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Economic Policy Uncertainty Effect on Precious Metal Markets: A Markov-Switching Model with Mixture Distribution Regimes

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Abstract : This paper examines the effect of economic policy uncertainty (EPU) on three precious metal markets (Gold, Silver, Platinum) using a Markov-switching model with mixture distribution regimes. Thirty six model specifications for each market are introduced here and the best model for each market is used for interpretation. Our results can be divided into two parts. First, we can confirm the persistence of the relationship between the economic policy uncertainty and the return of precious metal market. Second, as we doubt whether the regime in the model has a different distribution, the results confirm the existence of different distribution regime in the model. Thus, we can confirm different distribution characteristics between high and low economic uncertainty periods in precious metal markets.

Keywords : regime switching; mixture of distributions; economic policy uncertainty; precious metals.

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1 Introduction

Economic policy uncertainty (EPU) is the variable that contributes both a direct and an indirect effects to the economy. Baker [1] found this uncertainty shock reduced economic growth by 1.4 percent in 2011 and would reduce 2.3 million jobs within 19 months. This uncertainty can be measured by Economic policy uncertainty index. The index is based on newspaper coverage frequency and the evidence related to uncertain economic events appearing in the articles such as presidential elections in the USA, World War I and II, the 9/11 attacks, the failure of Lehman Brothers, the 2011 debt ceiling dispute, and other major battles over fiscal policy.

Many recent studies have investigated the impacts of EPU index on economy and financial market. For example, Kang [2] investigated the asymmetric response of gasoline prices to oil price shocks and policy uncertainty. They found the negative impact of the uncertainty shocks on the gasoline price. Arouri [3] and Roubaud [4] examined the impact of EPU shocks on oil prices, exchange rates, and stock markets using Markov Switching model. They also confirm the effect of EPU on these markets. They found that an increase in policy uncertainty significantly reduces the stock returns and the effect is stronger and persistent during extreme volatility periods. Interestingly, their results revealed the presence of the instability of the EPU's impact. Thus, this instability should not be ignored, and it would be reasonable to use the non-linear model to capture these distinct behaviors.

In this study, We, attempt to supplement the literature by examining the effects of economic uncertainty shocks on precious metal markets, consisting of gold, silver and platinum. These precious metals are attracted by many investors and are commonly included in their portfolios. Economists suggested that there is a close relationship between economic growth and precious metals. These precious metals are viewed as a great precursor for signalling economic growth and many investors consider it as a leading economic indicator to assess an economic condition in the future. In the literature, the study of the impact of EPU on precious metal markets is limited. There are some studies providing an evidence that economic uncertainty has a large impact on the gold price (Gao [5], Jones [6], Bouoiyour [7]. However, the empirical works that investigate the impacts of economic uncertainty on silver and platinum markets are very scarce. Therefore, this paper contributes to the literature by examining the effect of policy uncertainty on these two new markets. Moreover, as suggested by Arouri [3] and Roubaud [4], by allowing the mean to switch stochastically between different processes under different market conditions, one may obtain more robust estimates of the instability casual effects and, as a result, more efficient when compared to the linear model .Therefore, account the instability impact of EMU on precious metal markets using the Markov Switching regression model.

Nevertheless, Maneejuk [8] suggested that time series data often involves a mixture of distributions or populations, as a result of different characteristics of the data associated with different time, for example, distinct economic behaviors during economic upturn and downturn. Thus, they generalized the Markov Switching autoregressive by allowing the distribution of economic upturn and downturn states to be different. One main advantage of this proposed approach is that it allows for heterogeneous regimes, which is what we expect to yield better results than the conventional Markov Switching model. Undoubtedly, the distribution of the EPU should be different across economic regimes. This motivates us to consider this model in the regression context. Thus, the Markov Switching regression model with different distribution regimes is introduced and applied to study the impact of EPU on gold, silver and platinum markets.

Our study presents two main contributions compared to the previous works. First, we introduced a new empirical investigation of the effects of EPU on the various precious metal markets. Different form the previous studies, which were mainly focused on gold market, this study considers two more precious metal markets consisting silver and platinum markets. Second, as suggested by Maneejuk [8], our two-regime switching regression model is introduced to distinguish the impact of EPU on precious metal markets during high and low uncertainty periods, whereas the likelihood of high uncertainty may be different from the low uncertainty regime.

The remainder of this paper is divided into four sections as follows. Section 2 briefly explains the methodology, in which we review the concept and specific form of the simple Markov Switching model in the liner regression context, followed by the Markov Switching model with mixture distribution regimes and some explanations about the transmission regimes of parameters through Hamilton's filter, respectively. Section 3 presents the descriptive statistics of the data. Section 4 provides and discusses the main results of the empirical study. Finally, the concluding remarks and suggestions for future works are presented in Section 5.

2 Methodology

In this section, the casual effect of EPU on precious metal markets are modelled using a Markov Switching model with mixture distribution regimes. A Markov switching model is constructed by combining two or more dynamic models via a Markovian switching mechanism. We note that each model is assumed to have different distribution. Hence, the Hamilton's filter in Markov process is constructed by this mixing distribution.

2.1 A Markov-Switching (MS) Model

The linear regression model is a basic and commonly used model to predict the relationship between a dependent variable and one or more explanatory variables. The model can be written as

$$R_i = \alpha + \beta(EPU) + \varepsilon_i \tag{2.1}$$

where $R_i = (r_{i1}, ..., r_{iT})$ is the precious metal return i at time t,

$$EPU = (EPU_1, ..., EPU_t)$$

is an uncertainty variable and β is an unknown parameter with respect to EPU. The error term of the model $\varepsilon_i = (\varepsilon_{i1}, ..., \varepsilon_{iT})$ is vector which is assumed to have parametric distribution with mean zero and variance σ^2, for example normal, student-t, generalized error distributions. We transform the Eq. (2.1) that is the conventional linear regression model into the Markov-switching (MS) model with 2 distinct states as

$$R_i = \alpha_{S_t} + \beta_{S_t} EPU + \varepsilon_{i,S_t} \tag{2.2}$$

where $\varepsilon_{i,S_t} \sim i.i.d.(0, \sigma^2_{S_t})$. We note that the error distribution for each regime is different and, in this study, we consider six different distributions, namely normal, student-t, generalized error distribution (GED), skewed GED, skewed normal, and skewed student-t distributions. The formulation and brief explanation of these distributions will be provided in the further section. α_{S_t} denotes regime dependent intercept term and β_{S_t} denotes the regime dependent coefficients. The regime represented by $S_t = \{0, 1\}$ is considered as an unknown parameter. For two-regime model, the states are assumed to follow a first-order Markov process, with the following transition matrix:

$$\begin{aligned} P &= \left[\begin{array}{cc} \mathrm{P}(S_t = 0 \,|S_{t-1} = 0) & \mathrm{P}(S_t = 1 \,|S_{t-1} = 0) \\ \mathrm{P}(S_t = 0 \,|S_{t-1} = 1) & \mathrm{P}(S_t = 1 \,|S_{t-1} = 1) \end{array} \right], \\ P &= \left[\begin{array}{cc} p_{00} & p_{01} \\ p_{10} & p_{11} \end{array} \right], \end{aligned} \tag{2.3}$$

where p_{ij} is the probability of transition from regime i and j and $\sum_{j=1}^{H} p_{ij} = 1$.

The transition matrix governs the random behavior of the state variable S_t, and it contains only two parameters (p_{00} and p_{11}).

2.2 The MS Model with Mixture Distribution Regimes

This study aims to explain the impact of economic policy uncertainty on the precious metal markets under the assumption of different regimes in a Markov-switching model. We can write the complete likelihood function as,

$$L(\theta_{S_t} \,|R \,, \mathrm{EMU}) = \sum_{j=1}^{2} \left(\prod_{t=1}^{T} \left(f(\theta_{S_t = j} \,|R \,, \mathrm{EMU}) \right) \left(\Pr(S_t = j \,|\theta_{S_t}) \right) \right) \tag{2.4}$$

where $f(\theta_{S_t=j} \,|R_i, \mathrm{EMU})$ is the density function which can have different distributions across regimes. $\theta_{S_t=j}$ is a set of state dependent parameter of regime j where $\theta_{S_t} = (\beta_{S_t}, \sigma_{S_t}, P)$. More specifically, we consider 6 different distributions, namely normal, student-t, generalized error distribution (GED), skewed GED, skewed normal, and skewed student-t distributions. Thus, the density function $f(\theta_{S_t=j}|R_i, \text{EMU})$ in Eq.(2.4) can be written in 6 different forms according to the distribution being used.

Normal density

$$f_n = \prod_{t=1}^{T}\left[\sum_{S_t=1}^{h}\frac{1}{\sqrt{2\pi\sigma_{S_t}^2}}e^{\frac{-\varepsilon_{S_t}^2}{2\sigma_{S_t}^2}}\right] \tag{2.5}$$

Student-t density

$$f_t = \prod_{t=1}^{T}\left[\sum_{S_t=1}^{h}\frac{\Gamma(\frac{v_{S_t}+1}{2})}{\sqrt{(v_{S_t}-2)\pi\Gamma(\frac{v_{S_t}}{2})}}(1+\frac{\varepsilon_{S_t}}{(v_{S_t}-2)\sigma_{S_t}^2})^{\frac{-v_{S_t}+1}{2}}\cdot(\frac{1}{\sigma_{S_t}^2})\right] \tag{2.6}$$

where v_{S_t} is the state dependent degree of freedom.

Generalized error distribution density

$$f_{ged} = \prod_{i=1}^{T}\left[\sum_{S_t=1}^{h}\frac{\gamma_{S_t}\exp\left[-\left(\frac{1}{2}\right)\left|\frac{\varepsilon_{S_t}}{\lambda_{S_t}\sigma_{S_t}^{1/2}}\right|^{\gamma_{S_t}}\right]}{\sigma_{S_t}^{1/2}\lambda_{S_t}2^{(1+\frac{1}{\gamma_{S_t}})}\Gamma\left(\frac{1}{\gamma_{S_t}}\right)}\right] \tag{2.7}$$

where $\lambda_{S_t} = [(2^{-2/\gamma_{S_t}}\Gamma(1/\gamma_{S_t}))/\Gamma(3/\gamma_{S_t})]^{1/2}$.

Skew-t density

$$f_{sstd} = \prod_{i=1}^{T}\left[\sum_{S_t=1}^{h}\frac{2}{(\gamma_{S_t}+1)/\gamma_{S_t}}f_t(z/\gamma_{S_t}{}^{sign(z)}, v_{S_t})F\right] \tag{2.8}$$

such that $z = \frac{\varepsilon_{S_t}}{\sigma_{S_t}^{1/2}}F + \left[\frac{2\sqrt{v_{S_t}-2}}{(v_{S_t}-1)}\left(beta(0.5, \frac{v_{S_t}}{2})\right)^{-1}\right]\left(\frac{\gamma_{S_t}-1}{\gamma_{S_t}}\right)$, and

$F = \sqrt{1-\left[\frac{2\sqrt{v_{S_t}-2}}{(v_{S_t}-1)}\left(beta(0.5, \frac{v_{S_t}}{2})\right)^{-1}\right]^2\left(\frac{\gamma_{S_t}^2+1}{\gamma_{S_t}^2}\right)+2\left[\frac{2\sqrt{v_{S_t}-2}}{(v_{S_t}-1)}\left(beta(0.5, \frac{v_{S_t}}{2})\right)^{-1}\right]^2-1}$,

where γ_{S_t} is the skew parameter, *beta* is beta distribution and $f_t(\cdot)$is the density of student-t distribution.

Skew-normal density

$$f_{sn} = \prod_{i=1}^{T}\left[\sum_{S_t=1}^{h}\frac{2}{(\gamma_{S_t}+1)/\gamma_{S_t}}f_n(z/\gamma_{S_t}{}^{sign(z)})F\right] \tag{2.9}$$

such that $z = \frac{\varepsilon_{S_t}}{\sigma_{S_t}^{1/2}}F + \left[\frac{2}{\sqrt{2\pi}}\right]\left(\frac{\gamma_{S_t}-1}{\gamma_{S_t}}\right)$ and

$F = \sqrt{1-\left[\frac{2}{\sqrt{2\pi}}\right]^2\left(\frac{\gamma_{S_t}^2+1}{\gamma_{S_t}^2}\right)+2\left[\frac{2}{\sqrt{2\pi}}\right]^2-1}$, where γ_{S_t} is the skew parameter and $f_n(\cdot)$ is the density of normal distribution.

Skew-GED density

$$f_{sged} = \prod_{i=1}^{T} \left[\sum_{S_t=1}^{h} \frac{2}{(\gamma_{S_t}+1)/\gamma_{S_t}} f_{ged}(z/\gamma_{S_t}{}^{sign(z)}, v_{S_t}) F \right], \tag{2.10}$$

such that $z = \frac{\varepsilon_{S_t}}{h_{S_t}^{1/2}} F + \left[\frac{2}{\sqrt{2\pi}}\right]\left(\frac{\gamma_{S_t}-1}{\gamma_{S_t}}\right)$,

$$F = \sqrt{1 - \left[\frac{2^{1/v_{S_t}}(\lambda\Gamma(2/v_{S_t})}{\Gamma(1/v_{S_t})}\right]^2 \left(\frac{\gamma_{S_t}^2+1}{\gamma_{S_t}^2}\right) + 2\left[\frac{2^{1/v_{s(t)}}(\lambda\Gamma(2/v_{S_t})}{\Gamma(1/v_{S_t})}\right]^2 - 1},$$

$\lambda_{S_t} = \left[(2^{-2/\gamma_{S_t}}\Gamma(1/\gamma_{S_t}))/\Gamma(3/\gamma_{S_t})\right]^{1/2}$, where γ_{S_t} is the skew parameter and $f_{ged}(\cdot)$ is the density of GED distribution.

2.3 Hamilton's Filter

In 1989, Hamilton introduced Hamiltons filter [9] through the New Approach to the Economic Analysis of the Nonstationary Time Series and the Business Cycle. The Hamiltons filter refers to the prediction process for obtaining the unobserved variable S_t which is interpreted as a regime variable. It is also noted that we do never know which regime prevails at a certain point of time (Kole[10]). According to Eq. (4), the filter probability ($\Pr(S_t = j \,|\theta_{S_t})$) is an important part of the estimation. We need to filter out the estimated coefficient and variance into different regimes. Following Hamilton (1989), Hamiltons filter is determined using the following algorithm.

1. Make the calculating inference of transition probabilities P in Eq.(2.3)

2. Then update the transition probabilities of each regime with the historical information, including the parameters in the system equation (θ_{S_t}), and transition probabilities (P) for calculating the likelihood function in each state at time t, as shown in Eq.(2.4). The probability of each regime is updated by the following formula

$$\Pr(S_t = j \,|R_t, \mathrm{EMU}_t, \theta_{S_t}) = \frac{\begin{array}{c} f_j(R_t, \mathrm{EMU}_t \left| S_t = j, \theta_{S_{t-1}}\right.) \\ \times \Pr(S_t = j \left| R_t, \mathrm{EMU}_t, \theta_{S_{t-1}}\right.) p_{jj} \end{array}}{\sum_{j=1}^{2} \left\{ \begin{array}{c} f_j(R_t, \mathrm{EMU}_t \left| S_t = j, \theta_{S_{t-1}}\right.) \\ \times \Pr(S_t = j \left| R_t, \mathrm{EMU}_t, \theta_{S_{t-1}}\right.) p_{jj} \end{array} \right\}} \tag{2.11}$$

where $f_j(y_t \left| S_t = j, \theta_{S_{t-1}}\right.)$ is the likelihood function of regime j which is allowed to differ across regimes, and is filtered probabilities at time $t-1$. 3. Repeat step 1 and 2 for $t = 1, ..., T$.

To smooth the filtered probabilities, we follow the approach of Kim (1994) computing the smoothing probabilities which can be expressed as

$$
\begin{aligned}
&\Pr(S_t = j\,|R_t, \mathrm{EMU}_t, \theta_{S_t}) = \\
&\qquad \Pr(S_{t+1} = 0\,|R_t, \mathrm{EMU}_t, \theta_{S_t})\ \Pr(S_{t+1} = j\,|S_{t+1} = 0, R_t, \mathrm{EMU}_t, \theta_{S_t}) \\
&\qquad + \Pr(S_{t+1} = 1\,|R_t, \mathrm{EMU}_t, \theta_{S_t})\ \Pr(S_{t+1} = j\,|S_{t+1} = 1, R_t, \mathrm{EMU}_t, \theta_{S_t}) \\
&\qquad\qquad = \Pr(S_t = j\,|R_t, \mathrm{EMU}_t, \theta_{S_t}) \\
&\qquad \times \left(\frac{p_{j0}\Pr(S_{t+1}=0\big|R_t, \mathrm{EMU}_t, \theta_{S_t})}{\Pr(S_{t+1}=0\big|R_t, \mathrm{EMU}_t, \theta_{S_t})} + \frac{p_{j1}\Pr(S_{t+1}=1\big|R_t, \mathrm{EMU}_t, \theta_{S_t})}{\Pr(S_{t+1}=1\big|R_t, \mathrm{EMU}_t, \theta_{S_t})} \right)
\end{aligned}
\tag{2.12}
$$

Using the filtering probabilities $\Pr(S_t = j\,|R_t, \mathrm{EMU}_t, \theta_{S_t})$ as the initial value, we can iterate Eqs(2.11-2.12) backward to get the smoothing probabilities for $t = T-1, ..., t+1$.

3 Data Description

The data set for this study comprises weekly global economic policy uncertainty index and precious metal prices (Gold, Silver, Platinum) covering the period January 1999-September 2018. This data set is retrieved from Thomson Reuters database and Economic Policy Uncertainty website. We will transform a precious metal price into a log return. Table 1 shows the descriptive statistics for the economic policy uncertainty index and the log return of three precious metal prices. In the sample, the mean value of three precious metal data series is very close to zero. We observe that the Platinum has less variation than the others. Log return silver and platinum data series show negative skewness while EPU and gold have a positive skewness. In addition, all series have high kurtosis values (> 3). Therefore, we expect that our series exhibit non-normality.

The Jarque-Bera (J-B) test is considered to investigate the normal distribution property. However, with the ban of p-value in 2016, in this study, the statistical inference is based on the Minimum Bayes factor (MBF). Following Goodman [11] for alternative hypothesis, a BF10 between 1 and 1/3 is considered weak evidence, 1/101/3 moderate evidence, 1/301/10 substantial evidence, $1/100 - 1/30$ strong evidence, $1/300 - 1/100$ very strong evidence, and $< 1/300$ decisive evidence. The Minimum Bayes factor can be calculated from the Vovk [12] and Sellke [13] as follows.

$$
MBF(p) = \begin{cases} -\exp(1)p\log p & \text{for}\, p < 1/\exp(1) \\ 1 & \text{for}\, p \geq 1/\exp(1) \end{cases} \tag{3.1}
$$

where p is The P value and exp(1) has the value is approximately 2.71.

In this case, MBF values of Jarque-Bera test are close to zero. This indicates that there is decisive evidence for normal distribution. Also, the Augmented Dickey Fuller (ADF) test is conducted to show the stationarity of the data series. The results show the substantial and decisive evidence for stationarity.

Table 1: Descriptive statistics

	EPU	Gold	Silver	Platinum
Mean	111.7991	0.0059	0.0046	0.0034
Median	102.7707	0.0036	0.0046	0.0040
Maximum	245.1267	0.2356	0.2068	0.2383
Minimum	57.2026	-0.1760	-0.3761	-0.3192
Std. Dev.	35.6342	0.0511	0.0870	0.0688
Skewness	0.8361	0.1922	-0.3757	-0.4653
Kurtosis	3.2077	4.6473	4.3315	5.8216
Jarque-Bera	28.0414	28.2560	23.0826	87.1680
MBF	0.0000	0.0000	0.0000	0.0000
ADF-test	-2.8153 [a]	-17.4711 [b]	-17.0679 [b]	-9.1384 [b]

Note: [a] denotes the interpretation of MBF as substantial evidence and [b] denotes the interpretation of MBF as decisive evidence for stationarity,

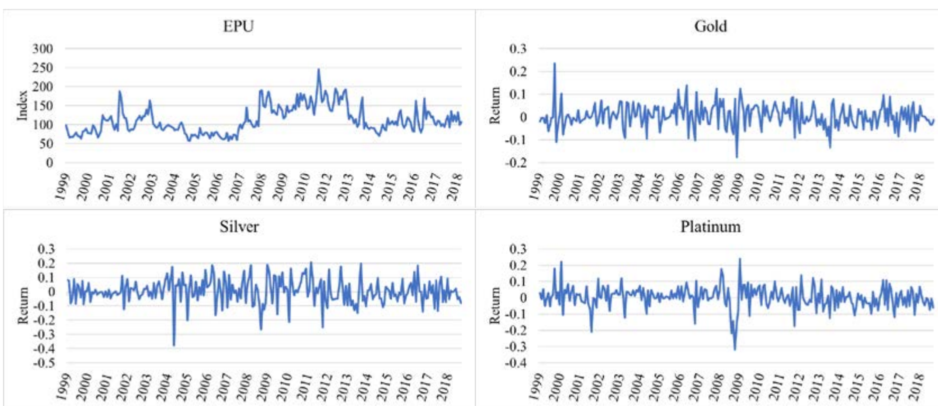

Figure 1: A time series data set for this study

4 Empirical Study

We examine whether economic policy uncertainty affects precious metal markets. First, we estimate a variety of MS specifications; 36 model specifications are first applied to estimate the effect of EPU on three precious metals. The best model for each case of precious metal is selected in terms of the lowest Akaike information criterion. Then, the best fit model is used to explain our results.

4.1 The Best Fit Model for Each Market

First, we consider a set of distributions to be a choice for the error distribution for each regime. Then, the best model among candidates is selected using (AIC) in such a way that the model with minimum AIC is statistically preferable. The six distributions consist of standard normal distribution (N), student-t distribution (T), generalized error distribution (GED), skew student-t distribution (ST), skew generalized error distribution (SGED), and skew normal distribution (SN).

Table 2: AIC of mixture MS models of Gold returns

Regime 2/	Regime 1					
Distribution	N	SN	T	ST	GED	SGED
N	-587.06*	-706.23	-636.10	-698.31	-703.00	-445.96
SN	-554.48	-478.69	-544.48	-546.85	-554.51	-478.61
T	-716.86	-676.16	-567.68	-672.53	-710.53	-672.63
ST	-714.86	-470.45	-568.87	-455.38	-634.76	-471.35
GED	-625.69	-550.09	-550.42	-591.39	-540.82	-541.01
SGED	-547.19	-474.93	-538.04	-540.12	-547.18	-475.51

Note: The processes are conducted under liner regression. * is the AIC value of the MS mixture model, where both regimes are based on normal distribution, corresponding to the ordinary MS model of Hamilton [9]. The underlined value is minimum AIC.

Consider a two-regime MS model for gold returns, the specific form is given by $R_{gold,t} = \beta_{0,S_t} + \beta_{1,S_t} Un_t + \sigma_{S_t} \varepsilon_{gold,t}$

where $R_{gold,t}$ is the gold return, β_{0,S_t} and β_{1,S_t} are intercept and coefficient, respectively. These two terms are regime dependent as well as the error. Table 2 shows the AIC values of MS with mixture model for gold return. From this table, we can see that the best fitting model is MS model with N-T distribution regimes; that is normal distribution is selected for regime 1 and student-t distribution is chosen for regime 2. The results show that the AIC value of the best-fitting mixture MS model, -716.86, is less than that of the classical MS-AR model, which is -587.06. This means the MS mixture model is more accurate and better than the conventional model.

Table 3: AIC of mixture MS models of Silver returns

Regime 2/	Regime 1					
Distribution	N	SN	T	ST	GED	SGED
N	-438.05*	-434.84	-478.44	-464.02	-435.33	-432.51
SN	-441.67	-414.45	-412.12	-409.47	-445.42	-411.80
T	-478.34	-474.33	-427.00	-427.69	-473.51	-472.07
ST	-460.11	-442.36	-414.09	-370.05	-449.49	-440.23
GED	-423.80	-423.45	-450.47	-459.99	-421.51	-420.95
SGED	-438.88	-412.51	-410.63	-407.68	-435.24	-409.87

Note: The processes are conducted under liner regression. * is the AIC value of the MS mixture model, where both regimes are based on normal distribution, corresponding to the ordinary MS model of Hamilton [9]. The underlined value is minimum AIC.

Consider a two-regime MS model for silver return, the specific model is written by $R_{silver,t} = \beta_{0,S_t} + \beta_{1,S_t}Un_t + \sigma_{S_t}\varepsilon_{silver,t}$

where $R_{silver,t}$ is the silver return, β_{0,S_t} and β_{1,S_t} are intercept and coefficient, respectively. The model selection result for silver return is provided in Table 4. Similar to the MS mixture model for gold return, the result shows high performance of the MS model with T-N distribution regimes; that is student-t distribution is selected for regime 1 and normal distribution is chosen for regime 2. The AIC values for silver return -478.44 which is the lowest value in the case.

Table 4: AIC of mixture MS models according to return of platinum

Regime 2/ Distribution	Regime 1 N	SN	T	ST	GED	SGED
N	-519.28*	-552.41	-577.92	-559.12	-511.57	-575.65
SN	-498.48	-497.79	-573.49	-544.26	-507.83	-493.87
T	<u>-573.63</u>	-553.58	-571.96	-548.55	-577.73	-548.74
ST	-565.94	-515.79	-571.17	-521.62	-568.36	-514.26
GED	-504.80	-513.45	-562.23	-540.20	-501.81	-510.22
SGED	-499.20	-489.94	-571.94	-542.75	-511.69	-484.76

Note: The processes are conducted under liner regression. * is the AIC value of the MS mixture model, where both regimes are based on normal distribution, corresponding to the ordinary MS model of Hamilton [9]. The underlined value is minimum AIC.

Finally, let's consider a two-regime MS model for platinum returns $R_{platinum,t} = \beta_{0,S_t} + \beta_{1,S_t}Un_t + \sigma_{S_t}\varepsilon_{platinum,t}$, where $R_{platinum,t}$ is the platinum return, β_{0,S_t} and β_{1,S_t} are intercept and coefficient, respectively. We find that the Markov mixture model with T-N distribution regimes also perform well for platinum case. According to these three market models, the results indicate that the state of economy appears to be distributed differently. Additionally, the study also discovers that the distribution of silver and platinum returns in regime 1 has heavier tails than regime 2, while the opposite result is shown in the gold market.

4.2 Parameters Estimates

In the next sub-section, the unknown parameters are estimated by the selected models. Table 5 shows the estimated parameters obtained from the mixture MS model for three markets. We can see that the intercept term of regime 1 for all equations are lower than regime 2, thus we interpret regime 1 as the high uncertainty regime while regime 2 is interpreted as low uncertainty regime. We note that regime 1 and 2 are perform different distributions as confirmed by the previous sub-section.

Table 5: Estimated parameters from the mixture MS-AR model

	Gold	Silver	Platinum
		Regime 1	
	Normal	Student-t	Normal
Intercept	-0.0312 ^{d} (0.0000)	-0.0083 ^{a} (0.7679)	0.0192 ^{d} (0.0000)
EPU	-0.0003 ^{d} (0.0000)	-0.0001 ^{a} (0.9596)	0.0002 ^{a} (0.8696)
Sigma	0.0501 ^{d} (0.0000)	0.1000 ^{d} (0.0000)	0.1000 ^{c} (0.0593)
Degree of freedom		2.5000 ^{d} (0.0000)	
Duration	23.31	19.9203	19.96
		Regime 2	
	Student-t	Normal	Student-t
Intercept	0.1367 ^{d} (0.0000)	0.0440 ^{d} (0.0000)	0.0401 ^{b} (0.1782)
EPU	0.0014 ^{c} (0.0411)	0.0003 ^{a} (0.3438)	-0.0004 ^{b} (0.1685)
Sigma	0.1000 ^{d} (0.0026)	0.1000 ^{d} (0.0000)	0.1000 ^{b} (0.1072)
Degree of freedom	2.5000 ^{d} (0.0000)		2.5000 ^{d} (0.0002)
Duration	19.96	19.96	
Transition matrix			
p_{11}	0.9571	0.9498	0.9501
p_{22}	0.9499	0.9499	0.9499

Note: ^{a} denotes the interpretation of MBF as weak evidence, ^{b} denotes the interpretation of MBF as moderate evidence, ^{c} denotes the interpretation of MBF as substantial evidence, ^{d} denotes the interpretation of MBF as decisive evidence.

For each market, the impact of EPU on these precious markets is quite different. In regime 1, we find that EPU has a decisive negative effect on gold market, while there is a weak evidence of the effect of EPU on silver and platinum markets. These results indicate that the high economic uncertainty lead to a lower return in gold market. For the second regime, low uncertainty regime, the similar results are shown. We observe that there is a decisive evidence supporting the effect of EPU on gold market. But the impact of EPU is positive. This result is important in showing that the importance of EPU varies by regime. This pattern is also observed only for the gold market. However, the impacts of EPU on silver and platinum markets are low with weak evidence support.

Furthermore, the transition matrix allows us to observe the probability of switching from one regime to another regime and remaining in its own regime. We find that in the case of gold, the high economic uncertainty regime has a duration of approximately 23.31 months, whilst the low uncertainty regime has only 19.96 months, approximately. The probability of staying in regime 1 is 95.71% but the probability of switching from regime 1 to regime 2 is 4.29%. Similarly, the probability of moving from low to high uncertainty is 5%, while the chance of remaining in the same state is 94.99%. In the case of silver and platinum, similar results are obtained. This indicates that the effect of EPU on precious metals are persistent for each regime.

In addition, Figures 2, 3 and 4 show the filtered and smooth probabilities plots for three markets. The Markov-switching model with a mixture distribution regime produces very clear state switching for all three markets, which are consistent with the staying probabilities p_{11} and p_{22}. The probability reflects the movement of return from precious metals that affected each the uncertainty event period. We find that in the case of gold market, there are high probabilities of uncertainty event in 2002 to 2004 and 2017 to 2018. The first period is 2002 to 2004, and this period corresponds to the invasion of Iraq or US-Iraq war and the second period, 2017 to 2018, corresponds to the Dow Jones share index closed at 4.6%, its biggest drop since the 2008 financial crisis. In the case of sliver market, the probability of staying in the high uncertainty regime is high along the sample period, except for the period 2000 to 2002 and 2013 to 2015. The first period is 2000 to 2002, which corresponds to the economic slowdown before the election in the USA. Investors were more interested in platinum and gold than silver, and thereby lowering the fluctuation of the silver. The second period is 2013 to 2015, corresponding to the shut down of the United States federal government. During this period, investors turned their attention to investing in gold market which is a major precious metal and thereby lowering the trade volume in platinum market.

In the last case of platinum, the probability of staying in the high uncertainty event regime is high only three periods, namely 2000, 2008 to 2010 and 2016. The first period 2000 corresponds to the election in the USA and the second period between 2008 and 2010 corresponds to the collapse of Lehman Brothers and debt ceiling dispute, while the last period in 2016 corresponds to the time the South African platinum miners being locked in collective wage negotiations and there was high demand for platinum in that period. Therefore, platinum prices tend to be volatile. A general pattern emerges from the analysis that indicates that the Markov Switching with mixture regime model delivers clear regime inferences for all markets, as the filtered and smoothed probability plots show clear evidence of switching between regimes.

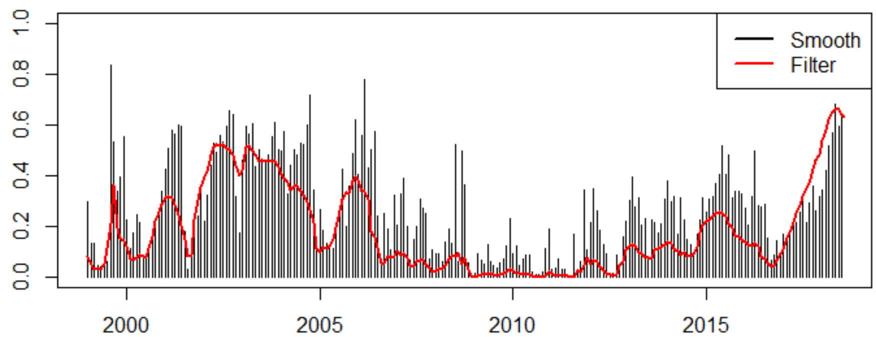

Figure 2: Filtered and Smoothed probabilities of high uncertainty regime for gold market

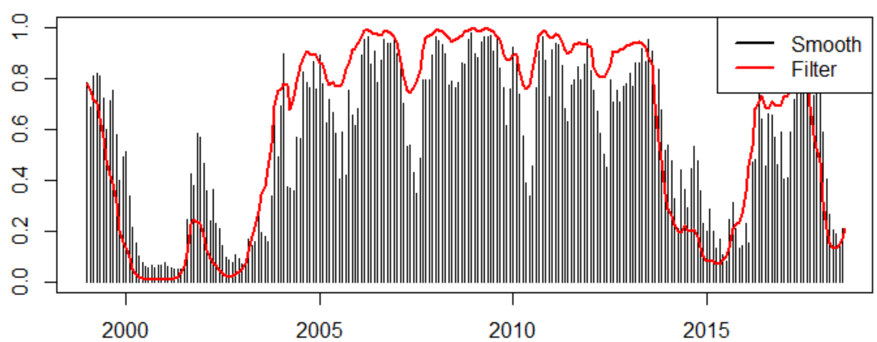

Figure 3: Filtered and Smoothed probabilities of high uncertainty regime for silver market

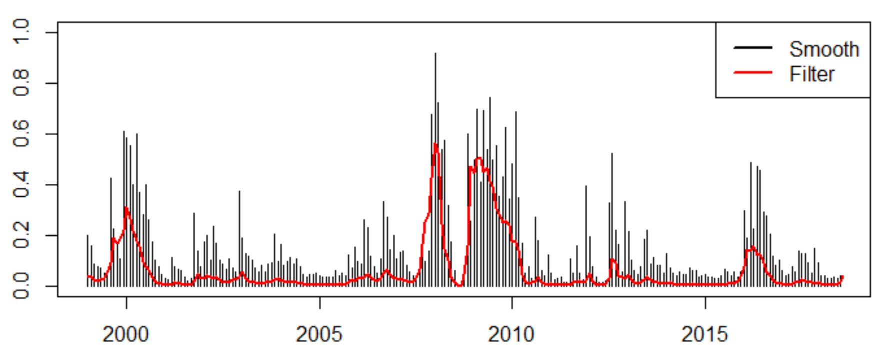

Figure 4: Filtered and Smoothed probabilities of high uncertainty regime for platinum market

5 Conclusion

There is a considerable literature looking at the impact of economic uncertainty on precious metals. This is an important topic to study because an economic uncertainty can influence the appetite of consumers around the world and the decision of the investors. However, the investigation of the impacts of the economic uncertainty on some of these markets are limited. This motivates us to investigate the impact of economic uncertainty on two new precious markets, namely platinum and silver. This study realizes the benefits of the Markov Switching with mixture distribution model for illustrating trend and fluctuation in these markets, particularly economic fluctuation or economic uncertainty.

Various model specifications are compared by AIC, and we find that a mixture distribution regime does exist for all markets. The student-t and normal distributions are the best fit distribution for the model, indicating the different characteristics of the two regimes of the economic uncertainty. The results demonstrate a clear effect of economic policy uncertainty only on gold market. We cannot obtain the strong evidence supportive of the impact of economic uncertainty on platinum and silver markets.

Nevertheless, this should deserve a further study. One of the things that should be improved in a future study is the use of a different models. Even though this study can prove the existence of the different distributions across regimes, but this is still limited to a set of specific distributions. The further study may consider other distributions for constructing the new combination of regime distribution.

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