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Using Markov-Switching Models to Identify the Link between Unemployment and Criminality[1]

by

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Abstract

Using Markov Switching Autoregressive models the behaviour of four crime variables and unemployment rate during the period of study is investigated and different regimes for each variable determined. Using some non-parametric measures such as the Concordance Index (Harding and Pagan, 2002) and Independence of Chronologies (Bodman and Crosby, 2005), among others, the independency of cycles of unemployment rate and crime variables is tested. The results of this stage show that there is no relationship between unemployment rate and burglary and motor. However, for larceny and robbery the results are mixed and inconclusive. At the second stage, Markov Switching Vector Autoregressive models are also used to determine the states for both unemployment rate and each one of crime variable simultaneously. The results of this stage show that the effect of unemployment rate on larceny and motor depends on the state of the variables. For larceny this effect is either positive or null, and for motor it fluctuates among negative, null, and positive. Also the result shows that regardless of the state of the variables, the effect of unemployment on burglary and robbery is negative and null, respectively.

Keywords: Markov-Switching Models, Cycles, Asymmetries, Unemployment, Crime.

JEL Classification: C22

Résumé

Nous utilisons des modèles de changement de régime pour analyzer le comportement du taux de chômage et quatre séries de criminalité. On utilise quelques mesures non-paramétriques telles que l'indice de concordance (Harding et Pagan, 2002) et l'indice d'indépendance des chronologies (Bodman et Crosby, 2005). Les résultats démontrent qu'il n'existe pas de relation entre le taux de chômage et le cambriolage et le vol des véhicules motorisés. Cependant, pour le vol et le pillage les résultats sont pas concluants. En la deuxième étape, des modèles des vecteurs autoregressives avec des changement des régimes sont utilisés pour déterminer les états du taux de chômage et chacune des variables de criminalité de façon simultanéee. Les résultats montrent que l'effet du taux de chômage sur le vol et le vol de véhicules motorisés sont dependant de l'état des variables. Pour la variable vol, l'effet est positif ou négatif. Pour le vol de véhicules motorisés l'effet est négatif, null et positif. Aussi, les résultats montrent que peu importe l'état des variables, l'effet du chômage sur le cambriolage et le pillage est négatif et null, respectiveent.

Mots-clés: Modèle à changement de regimen, Cycles, Asymmetries, Chômage, Crimen.

Code JEL: C22.

1 Introduction

Although the economic theory anticipates the existence of a positive relationship between unemployment and crime, the empirical works in this regard found mixed results. Chiricos (1987) reviewed 68 studies about the relationship between crime and the unemployment rate and he found that only less than half of these studies have found positive significant effects of the unemployment on crime rates. That is, most of these studies show a negative or no relationship between crime and unemployment.

Some authors argue that the source of disagreement among the results comes from the type of data that has been used; see Kapuscinski, Braithwaite, and Chapman (1998).

Cook and Zarkin (1985) presented an analysis of the business cycle and its impact on homicides, robbery, burglary, and auto theft using U.S. data for the period 1933-1981. Using a nonparametric test based on the changes in criminal activity during the entire business cycle, they showed that an increase in robbery and burglary is higher during economic contractions than expansions. Furthermore, more auto theft occurs during expansions relative to contractions. Using other set of tools, they found a positive relationship between the unemployment rate and robbery and burglary but this effect was negative for auto theft.

Hale and Sabbagh (1991) investigated the effect of unemployment on eight types of crime in England and Wales. They found that there is a significant relationship between unemployment and five kinds of crime. Their results also show that there is no relationship between the unemployment and auto theft. Property crimes including theft, burglary, and robbery had positive relationships with changes in the unemployment rate. Robbery had negative relationship with changes in the unemployment rate at the previous period.

Using age-specific arrest rates and an age-specific unemployment rate, during 1958-1995, Britt (1997) found that unemployment has negative effect on homicide and aggravated assault for the younger age groups and it was positive for older age groups. Witt, Clarke and Fielding (1999) found a positive relationship between crime and the male unemployment rate.

Entrot and Spengler (2000) used panel data methodology to study the effect of socio-economic factors on crime. They used two data sets, one only for West Germany and the other for unified Germany. The result of the first data set shows that the effect of the unemployment is small, often insignificant, with ambiguous signs. On the other hand, the results from a unified Germany (1993-1996) indicate that the impact of the unemployment becomes higher and unambiguously positive.

Greenberg (2001) used time series data, cointegration, and error correction models to investigate the relationship between divorce rates and unemployment on robbery and homicide rates in U.S. He concluded that lagged values of unemployment and unemployment duration have a negative effect on robbery. His finding is consistent with the finding of a previous study by Cantor and Land (1985). Raphael and Winter-Ebmer (2001) analyzed U.S. data and their findings show that the unemployment rate has a significantly positive effect on property crimes, but not on the violent crimes.

The same conclusion is obtained by Levitt (2001) using a state-level panel of annual data for the period 1950-1990 in U.S. Imerohoroglu et. al. (2004) analyzed the trends in the aggregate property crime rate in the U.S. for the period 1975-1996, using a dynamic equilibrium model. They tried to investigate the factors that determine the pattern of this kind of crime. They found a negligible effect of the unemployment rate on crime. Edmark (2005) using a panel of Swedish counties over 1988-1999 shows that there is a strong positive relationship between the unemployment rate, burglary, car theft and bike theft.

Recently Lee and Holoviat (2006) have used cointegration approach to identify for a long run relationship between unemployment and a set of crime variables in three Asian-Pacific countries. They find a long-run relationship, in particular between unemployment of young males and crime.

Most of these studies were carried out using multiple regression models, vector autoregression or error correction models. All of these methods assume a stable behavior of the variable under examination. Nevertheless, the unemployment rate directly correlated to business cycle has a cyclical pattern and linear models cannot explain its behavior. Consequently, one needs to use non-linear models. As publicized by Hamilton (1989), Markov

Switching (MS) models have the capability to capture changes in the behavior of time series by allowing the switching between regimes or states. The MS models have been used widely in the literature and have proven their ability to explain the changes in pattern of time series. Hamilton (1990) introduced the expectation maximization (EM) algorithm for estimating the parameters of these kind of models. Kim (1994) extended the concept of the MS model to state-space models and suggested an approximate smoothing algorithm. Albert and Chib (1993) proposed Gibbs sampling method. Some authors tried to extend the original model proposed by Hamilton (1989) by including time-varying or duration dependent transition probabilities. For example, Durland and McCurdy (1994) studied the duration dependent case and Filardo and Gorden (1998) estimated transition probabilities as a function of exogenous information.

This paper has two goals. The first goal is to study the behavior of different types of crime and the second goal deals with the potential relationship between the unemployment rates and the different crime rates in the U.S. The period of the study is 1975:1 until 2004:4 and four types of crimes are analyzed: burglary, larceny, motor-vehicle theft (motor), and robbery.

The Markov-Switching methodology is used to investigate the behavior of the unemployment rate and crime variables and link them, using the data above mentioned. The remaining portion of this paper has been organized in two phases. The first phase consists in using MS-AR models to investigate the behavior of the crime variables and the unemployment rate during the period of study and determine different regimes for each variable. After that, using some non-parametric measures such as the Concordance Index (Harding and Pagan 2002) and the Independence of Chronologies (Bodman and Crosby 2005), the independency of cycles of the unemployment rate and crime variables is tested. In the second phase, the Markov-Switching Vector Autoregressive models will be used to determine the states for both the unemployment and crime variable simultaneously. These models will also be used to investigate the effect of unemployment on crime variables at different regimes of these variables. The reason for using this method is that maybe the unemployment rate influences the crime rates differently in separate states and disregarding this fact is the cause of mixed results in previous studies.

2 Methodology

The switching models was motivated by Quandt (1972), Goldfeld and Quandt (1973). It has been popularized by Hamilton (1989) with an application to business cycles. In the switching model introduced by Quandt (1972) the switching mechanism is independent from each other, while at the switching model of Quandt and Goldfeld (1973) and Hamilton (1989), these switching are governed by a first order Markov chain . They are known as MS models.

Consider a case that one wants to study the behavior of a single[3] stationary variable y_t, and assume that the realized values of this variable for $t = 1, 2, ..., T_1$ can be described with a first-order autoregression:

$$y_t = c_1 + \rho_1 y_{t-1} + \epsilon_t \tag{1}$$

where $\epsilon_t \sim N(0, \sigma^2)$. Now assume that there is a jump or structural change in this variable at time T_1 and the new model to describe the behavior of y_t is

$$y_t = c_2 + \rho_2 y_{t-1} + \epsilon_t \tag{2}$$

for $t = T_1 + 1, T_1 + 2, ..., T$. These two models could be compress into one equation using a dummy variable D_t. In this case the following model can be used to explain the behavior of y_t:

$$y_t = c_1 + \rho_1 y_{t-1} + \delta D_t + \gamma D_t y_{t-1} + \epsilon_t, \tag{3}$$

where the variable D_t takes values of 0 and 1 for $t < T_1$ and $t \geq T_1$, respectively.

The other compact way to represent this variable is

$$y_t = c_{s_t} + \rho_{s_t} y_{t-1} + \epsilon_t, \tag{4}$$

[3]Although the case of a single variable is discussed here, everything may be used for more than one variable.

where s_t takes values of 1 and 2 and it shows the period before and after change in y_t, respectively. In other words, the period $t < T_1$ is represented by $s_t = 1$ and the period after jump, $t \geq T_1$ by $s_t = 2$.

Nevertheless, these methods have three shortcomings. First, the exact date of the jump has to be known priori to be able to use the dummy variable. Second, it is not satisfactory to use this model to forecast the behavior of y_t. The other shortcoming is that s_t is treated as a deterministic variable and is perfectly predictable, which is not a realistic assumption.

Therefore, to solve these problems and to complete the data generating process one needs to include a description of the probability law for s_t. In the MS model, the switching mechanism is controlled by an unobservable state variable called s_t. This state variable follows a first order Markov chain. In other words, the value of this state variable at period t depends only on its value at period $t - 1$[4].

The switching model for y_t is given by

$$y_t = \left\{ \begin{array}{l} c_1 + \rho_1 y_{t-1} + \epsilon_t, \ \ s_t = 1 \\ c_2 + \rho_2 y_{t-1} + \epsilon_t, \ \ s_t = 2 \end{array} \right\}.$$

Therefore, this model shows two different dynamic structures, depending on the value of the state variable s_t. Different assumptions about s_t generate different models. When $s_t = 1$ for $t = 1, 2, ..., T_1$ and $s_t = 2$ for $t = T_1+1, T_1+2, ..., T$, this model is nothing but a model with single a structural change at time T_1. When s_t are independent Bernoulli random variables, this model shows the random switching model of Quandt (1972). If s_t is considered as an indicator variable such that $s_t = 1$ or $s_t = 2$ respectively for $\theta \leq c$ and $\theta > c$, where c is the threshold value, this model becomes a threshold model. When s_t follows a Markov processes this model is the MS model.

In the MS model, the properties of y_t are determined jointly by the characteristics of ϵ_t and the state variable s_t. The state variable generates random and frequent changes in pattern of the model. To have full dynamics of the variable, a probabilistic description of how the variable s_t moves from

[4] Since the realization of the state variable is not directly observable, sometimes these models called Hidden Markov models.

one state to another is needed. First order Markov chain indicates that these probabilities are:

$$\Pr[s_t = j | s_{t-1} = i, s_{t-2} = k, ...; y_{t-1}, y_{t-2}, ...] = \Pr[s_t = j | s_{t-1} = i] = p_{ij}.$$

The transition between states or regimes can be represented using a transition probability matrix. For a simple model, which has only two regimes, this matrix is

$$\begin{aligned} P &= \begin{bmatrix} Pr(s_t = 1 | s_{t-1} = 1) & Pr(s_t = 2 | s_{t-1} = 1) \\ Pr(s_t = 1 | s_{t-1} = 2) & Pr(s_t = 2 | s_{t-1} = 2) \end{bmatrix} \\ &= \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}, \end{aligned}$$

where p_{ij} $(i, j = 1, 2)$ indicates the transition probabilities of $s_t = j$ given that $s_{t-1} = i$ and $p_{i1} + p_{i2} = 1$.

There are different ways to estimate the MS models. For example, the maximum likelihood estimation (MLE) of Hamilton (1989), the expectation maximization (EM) algorithm proposed by Hamilton (1990), and the Gibbs sampling approach of Albert and Chib (1993). See also Krolzig (1997) and Kim and Nelson (1999). The EM algorithm has been designed to estimate the parameters of a model where the observed time series depends on an unobserved or a hidden stochastic variable. As mentioned earlier, y_t is directly observable but state variable is unobservable and one can only make inference about its value based on the realization values of y_t. This inference could be shown as $\xi_{it} = \Pr[s_t = 1 | \Omega_t; \theta]$, for $i = 1, 2$, where Ω_t shows the information set (i.e., set of the observations available at period t) and θ is the vector of parameters to estimate. To make inference, one should use iterative method for $t = 1, 2, ..., T$, while taking the previous value of this probability $\xi_{it-1} = \Pr[s_t = 1 | \Omega_{t-1}; \theta]$ as input.

In order to perform the iteration the densities under the different states are needed. They are given by

$$\begin{aligned} \eta_{it} &= f(y_t | s_t = i, \Omega_{t-1}; \theta) \\ &= \frac{1}{\sqrt{2\pi}\sigma} \exp[-\frac{(y_t - c_i - \rho y_{t-1})^2}{2\sigma^2}]. \end{aligned}$$

The conditional density of the $t-th$ observation can be calculated as

$$f(y_t|\Omega_{t-1};\theta) = \sum_{i=1}^{2}\sum_{j=1}^{2} p_{ij}\xi_{jt-1}\eta_{it},$$

and therefore:

$$\xi_{it} = \frac{\sum_{j=1}^{2} p_{ij}\xi_{jt-1}\eta_{it}}{f(y_t|\Omega_{t-1};\theta)}.$$

Using these results and iteration one can get the conditional log likelihood of observed data as following:

$$Log\ f(y_1, y_2, ..., y_T|y_0;\theta) = \sum_{t=1}^{T} Log\ f(y_t|\Omega_{t-1};\theta)$$

for the given values of θ. To obtain the estimation of θ, numerical optimization is used to maximize the conditional log likelihood using some starting values for ξ_{j0}. Assuming that the Markov chain is ergodic[5] the unconditional probabilities can be used as initial values. They are defined by

$$\begin{aligned}\xi_j &= \Pr[s=j] \\ &= \frac{1-p_{ii}}{2-p_{ii}-p_{jj}}.\end{aligned}$$

Once the coefficients of the model are estimated and transition matrix is calculated, one can calculate the probability of being in state j at each period of time, based on the information of the whole sample. This series of probabilities is known as smoothed probabilities. In addition, one can calculate the probability of being at state j at each time only based on the information up to that date (not whole sample), known as filtered probabilities.

In practice, there are several options concerning the regime-dependency of the parameters. These regime-dependent parameters could be the intercept (I), the autoregressive coefficients (A), the variance (H), or their combinations. For example, a MSI model denotes a MS model with regime

[5] Its transition matrix has at least one eigenvalue equal to unity. Recall that the two regime Markov chains are ergodic, provided that $p_{11} < 1$, $p_{22} < 1$, $p_{11} + p_{22} > 0$,

dependent intercept. A MSIA model denotes a MS model where the intercept and the autoregressive coefficients are regime dependent.

The MS models have been used particularly in modeling business cycles. One interesting issue in this context is the analysis of asymmetries. There exists different measures of asymmetries depending whether the model is parametric or non parametric. In the last case, the most popular measures of asymmetries are steepness, deepness, and sharpness. Sichel (1993) defined an asymmetric cycle as one in which some phases of the cycle are different from the mirror image of the opposite phase[6].

Consider a stationary univariate process y_t with mean μ_y and standard deviation σ_y. The process y_t is called symmetric if the following condition holds for all $\varepsilon \in \Re$:

$$\Pr[y_t < \mu_y - \varepsilon] = \Pr(y_t > \mu_y + \varepsilon].$$

In the literature on asymmetries, different ways have been suggested for testing for steepness and deepness. Sichel (1991) suggests the use of the skewness as an indicator of asymmetry. Therefore, it is defined by

$$\tau_y = \frac{E[y_t - \mu_y]^3}{\sigma_y^3}.$$

One can infer about the type of asymmetry based on the sign of τ_y. The type of this asymmetry is named deepness if $\tau_y < 0$. There is tallness if $\tau_y > 0$.

Steepness of the distribution deals with the changes in the process over time, namely Δy_t. Since y_t is assumed to be stationary therefore, $\mu_{\Delta y} = 0$ and to satisfy the symmetric condition the following must hold for all $\varepsilon \in \Re$:

$$\Pr[\Delta y_t < -\varepsilon] = \Pr[\Delta y_t > \varepsilon].$$

Similarly, the degree of asymmetry can be measured by using the skewness coefficient of Δy_t. It is denoted by $\tau_{\Delta y}$. This coefficient shows that

[6] Other types of asymmetry such as asymmetric persistence to shocks (see Hess and Iwata, 1997) and duration dependence (see Sichel, 1991, Filardo and Gordon, 1998) are widely used in the parametric models.

when $\tau_{\Delta y} < 0$ the asymmetry exists and is called negative steepness. On other hand, $\tau_{\Delta y} > 0$ shows positive steepness.

Neftci (1984) used the duration of increases and decreases as an indicator for steepness of the time series. When the duration of increases is higher than the duration of decreases in the time series, the contractions are for sure steeper than the expansions.

The last kind of asymmetries for the non-parametric models is sharpness which has been introduced by McQueen and Thorley (1993). If the shape of troughs and peaks are not the same and one of them is round and the other is sharp, this form of asymmetry will exist in the time series. According to them, a process is non-sharp if and only if the condition $p_{n1} = p_{nN}$ and $p_{1n} = p_{Nn}$ is satisfied for all $n \neq 1, N$; and $p_{1N} = p_{N1}$. So, in a two state model, non-sharpness requires to have $p_{12} = p_{21}$. In a MS model with three regimes, non-sharpness is obtained if $p_{12} = p_{32}$, $p_{13} = p_{31}$, and $p_{21} = p_{23}$.

3 Data

For this study, quarterly data of four crimes series (Burglary, Larceny, Motor-Vehicle Theft, and Robbery) for the U.S. is used. The data is obtained from the Uniform Crime Reports of the Federal Bureau of Investigation (FBI). This data consists of 120 observations for the period of 1975:1 to 2004:4, and shows the number of each crime per 100,000 of population. The data for the quarterly unemployment rates is taken from the Bureau of Labor Statistics.

The data is seasonally non-adjusted. We use the TRAMO/SEATS procedure of Gomez-Maravall (1992) to remove the seasonality and detect the presence of outliers in the series.

The presence of unit roots is formally tested by using the ADF, GLS-based Augmented Dickey-Fuller statistic, and the feasible point optimal statistic suggested by Elliott, Rothenberg, and Stock (1996). The null hypothesis of a unit root is not rejected for any of the crime series. It means that all crime time series are I(1) processes. On the other hand, the unemployment rate appears to be stationary, that is, I(0).

4 Empirical Results of the Univariate MS-AR Models

Given previous results of the unit root tests, the crime series are modeled in first differences and the unemployment rates enters in level. A generalized version of the model suggested by Hamilton (1989) has been estimated. All estimations have been carried out using the MSVAR class for Ox by Krolzig (1997).

Before estimating the MS models, a linear model is specified. The lag length is determined by using information criteria such as AIC, BIC, and HQ. Using the selected lag structure, MS models with two and three states are estimated, allowing for changes in the intercept, variance and autoregressive parameters. Based on the information criteria and the LR statistic, we select the best MS models. The null hypothesis of linearity is rejected for all selected models.

As Krolzig (1997) argues, there is not any general test to compare two models with different number of regimes. The issue is that the asymptotic theory cannot be used because of the presence of unidentified nuisance parameters and violation of the non singularity conditions.

A close examination of these models reveals that the selected models for burglary, larceny, and robbery can satisfactorily capture the movement of these series. However, the selected models of motor-vehicle theft and the unemployment rate do not fit well, so other models were selected to be able to explain the movements of these series.

4.1 Burglary

For this time series two MS models have been selected. The two selected MS models for burglary rates are the MSIH(2)-AR(1) and the MSIH(3)-AR(8). Table 1 shows results for the model MSIH(2)-AR(1). This model strongly rejects the null hypothesis of linearity. Notice that the t-ratio of the first intercept is close to the bound of 10.0% level of significance. Overall, the model shows that at the first regime, a decrease in the rate of burglary is present, and in the second regime, this rate increases or remains constant. Therefore, the first regime stands for lower and the second regime is for higher burglary rates in the U.S.

Based on the transition probabilities, it is clear that both regimes are very persistent with probabilities of 90% and 96%, respectively for the first regime (lower burglary rates) and the second regime (higher burglary rates). In addition, the unconditional probabilities of being at the lower and higher burglary rate regimes are 29% and 71% respectively. The transition probabilities reveal that the duration of the first regime is 10.2 quarters, whereas the second regime has a duration of 24.7 quarters. This indicates the presence of asymmetries in duration of the regimes of lower and higher burglary rates. It means that the periods of reduction in the rate of burglary are much shorter than the periods with positive change at this rate.

The results also show that only 34% of the observations for burglary are categorized in the first regime. It means that between the second quarter of 1977 and the end of 2004, in only 37.6 quarters the rate of burglary was declining. Concerning the standard errors, the model allows for different variances for each regime. In fact, the result shows that the second regime is much less volatile than the first regime (standard error of 9.46 compared to 22.6).

The smoothed probabilities and the filtered probabilities of being at each regime at each point of time are visualized at Figure 1a. It shows that the first regime (lower burglary rates) is formed by the periods 1977:2-1981:3, 1983:4-1985:1, and 1988:3-1990:3. The same figure also shows that observations since 1990:4 until the end of the sample form the second regime (higher burglary rates).

Testing for asymmetries, we obtain that the hypothesis of non-sharpness, non-deepness, and non-steepness cannot be rejected for this model. Therefore, the cycles are symmetric.

The other selected model is the MSIH(3)-AR(8). In this case we have three regimes and a larger lag structure. The null hypothesis of linearity is again strongly rejected. As in the previous model, this model allows for heteroscedasticity among the regimes. Table 1 presents the results. The first two regimes have negative intercepts, however, the first one is not significant so the first regime shows the periods with no significant changes at the rate of burglary and the second regime stands for the periods with negative changes at the rate of this kind of crime. The third regime has positive intercept and stands for higher burglary rates. In this model, all the autoregressive coefficients are statistically significant.

The transition probabilities show that the third regime (higher burglary rates) is the most persistent regime with a probability of 94%, and the second regime (lower rate) is less persistent with 35%. Furthermore, there is a 25% chance to move from the first regime (constant rate of burglary) to the second one and only 2% to move to the third regime. Therefore, probability to move to the third regime is low, but when state is there, this regime is very persistent and has a long duration. Moreover, if this variable is at the second regime at time t, there is higher chance to move to the first regime than to the third regime. As for the third regime, the probability of moving from this regime to the second regime is only 0.02%; this indicates that the burglary rates almost never changes from the third regime to the second one directly. In other words, if there is a positive change in the burglary rates at any period, then it would be very unlikely to see any decreases in this rate at next period.

As in the previous model, the third regime (higher burglary rates) has the longest duration and it continues more than 17 quarters, while the second regime lasts less than two quarters. These duration periods can be translated to the share of each regime in sample; the higher the duration the higher is the share of that regime. In this case, 33% of observations are contained in first regime, 54% in third regime, and only 13% are contained in the second regime. Therefore, in most of the period under study burglary was high in the U.S.

According to the standard errors of the regimes, it is observed that the first regime has the highest volatility (21.37) and the second regime the lowest (0.33). At the same time, the standard error of the third regime is 8.5.

The Figure 1b shows the smoothed and the filtered probabilities of being at each regime. It is observed that the burglary rate fluctuates among regimes between 1977:2 and 1993:3. However, it has stayed at the third regime since 1993:4, which means that there was not any significant decline at the rate of burglary since this period.

Tests of asymmetry (with a χ^2 values of 0.712, 0.268, and 0.900, respectively) do not show any evidence of asymmetries in cycles. Therefore, different duration of regimes is the only source of asymmetry for this variable.

4.2 Larceny

Application of the TRAMO/SEATS procedure of Gomez and Maravall (1992) indicates the presence of an outlier at the observation 2003:2. A dummy variable (impulse type) is used to take into account for this observation.

All information criteria indicate that the preferred model is the MSI(2)-AR(1). Notice that this is the simplest MS model. This model has only two regimes, no heteroscedasticity and a simple lag structure.

Table 1 presents the results for this model. The results show that the first regime has a negative intercept, the intercept of the second regime is positive and both of them are significant. The coefficient of the dummy variable for the outlier is negative and significant. According to these results, the first regime stands for the periods with decreasing rates of larceny and the second regime shows the periods with increasing rates of larceny.

The durations of the regimes are 2.93 and 12.17 quarters, respectively. From 111 observations included in the estimation, the first regime accounts for only 20% of the observations (22.6 quarters) while the second regime accounts for 88.4 quarters. The transition probabilities indicate that the second regime is more persistent than the first regime with a probability of 92% compared to 66%, respectively. It means that, if there is an increasing rate of larceny at any period, it will be very difficult to return to a regime with a decreasing rate. The unconditional probabilities of being at the regimes with lower and higher rates of larceny are 19% and 81% respectively.

The Figure 2 shows the smoothed and the filtered probabilities of larceny in the two regimes. According to these results, the first regime is conformed by the periods 1977:2-1978:1, 1980:1-1980:4, 1991:1-1991:2, 1996:4-1997:1, 2001:1-2002:1, 2004:2-2004:3. Notice that most of these periods last only for two quarters.

The values of the χ^2 statistic for the hypothesis of non-sharpness and non-deepness are 6.3 and 5.8, respectively. It means that the null hypothesis can be rejected in favor of the alternative. Consequently, the cycles are not symmetric on these features. However, there is no evidence of steepness.

4.3 Motor-Vehicle Theft

For this variable, the AIC and the LR test suggest that the best model is a MSIAH(2)-AR(1). However, as mentioned earlier, a close investigation of this model reveals that it does not fit the data and it cannot capture the movements of this time series. At the same time, the SIC suggests a MSI(2)-AR(1) as the best model which matches the data and its movement well. Therefore, this model is selected as the best model for the motor- vehicle theft variable.

Table 1 shows the results for this model. The intercepts are negative and positive respectively for the first and second regimes. However, only the second intercept is significant. The coefficient of the lagged variable is not significant. The first regime shows the periods with negative change at the rate of motor-vehicle theft, and the second regime stands for the periods with positive changes of this rate.

Both of the regimes are very persistent and there is a 4% probability of moving from the first (lower rates of motor-vehicle theft) to the second regime (higher rates of motor-vehicle theft). The opposite direction has an 8% probability.

The results also indicate that 35% of the observations are classified in the higher rate regime. The expected duration of this regime is 13 quarters compared to 24 for the first regime.

The Figure 3 shows the smoothed and the filtered probabilities of being at each regime. It shows that periods 1978:2-1983:1, 1990:4-2000:1, and since the second quarter in 2002, the variable is at the first regime. That is, the change at the rate of motor-vehicle theft in the U.S is negative. For the rest of the sample, the changes in motor-vehicle theft have been positive and the rate of motor-vehicle theft was higher.

According to the tests for asymmetry, all the cycles are symmetric at 5% level of significance.

4.4 Robbery

Two additive outliers are identified by using the procedure TRAMO/SEATS. They are located at observations 1993:1 and 1994:1. All information criteria select the model MSIH(2)-AR(1).

Table 1 presents the estimates. The first regime stands for all the periods with negative changes at the rate of robbery (lower robbery rates) and the second regime shows all the periods with positive changes in this rate (higher rates of robbery).

The second regime is more volatile than the first regime. It is reflected by the corresponding standard errors. The expected durations are 9.0 and 6.8 quarters, respectively for the first and second regimes. The lower robbery rates regime includes 67% of the observations (62.6 quarters). Transition probabilities indicate that both of the regimes are persistent, with probabilities equal to 89% and 85%, respectively. It means that if there is a negative change (positive change) in this rate at any period, then there is a high probability to have a negative change (positive change) at the next period.

The Figure 4 visualizes the smoothed and the filtered probabilities for both regimes. The longest period with a decreasing rate of robbery is 1993:4-2002:1, which contains 34 quarters. The rest of the study period is oscillating between the regimes.

The only form of asymmetry is the different durations. All the other asymmetry tests indicate symmetry of the cycles, indicating that the cycles are not sharp, deep, or steep.

4.5 Unemployment Rate

Although the information criteria have selected the MSI(2)-AR(3) and the MSI(3)-AR(3) as the best models, they can not capture the movements of the series. The model that can fit the data well and describe the changes of the unemployment rate in the U.S. is the MSIAH(2)-AR(3). The LR linearity test strongly supports the non-linearity in this variable.

The Table 2 shows the results of estimation of this model. This model allows for regime dependent autoregressive parameters and variance, so there are different estimations for coefficients of lagged variables in regimes. The estimated standard errors are 0.119 and 0.285, respectively, for regime one and two. Therefore, the regime with higher unemployment rates is more volatile than the first regime.

Regime one shows all the periods with negative changes at the unemployment rate in the U.S and the second regime stands for all the periods with positive changes at this variable.

The expected duration of low unemployment is almost three times larger than the duration of higher rates of the unemployment. During the period of study, 79 quarters form the regime of low unemployment rate and the rest (32 quarters) is classified as the second regime (higher unemployment). Regime one is more persistent than the second regime based on the transition probabilities, with probabilities of 94% and 84% respectively to stay at the same state at the next period.

The Figure 5 shows the smoothed and the filtered probabilities for both regimes. The only periods with high unemployment rates are 1979:1-1984:3, 1990:3-1992:1 and 2001:1-2001:4. These periods almost perfectly corresponds to the recession periods in U.S. At the rest of study period the unemployment rate in the U.S. was at a lower regime.

5 Synchronization of Cycles

So far, MS models for each single time series has been estimated and the properties of them, such as expected durations, transition probabilities, and asymmetries have been investigated individually. One of the questions of interest in this paper is the existence of any relationships between the unemployment rate (as an indicator of the condition of the economy) and the crime variables. In order to answer this question one can test whether the timing of the cycles of the unemployment rate and the crimes under study in this paper are similar or not. In other words, one can check for synchronization of cycles; that is, to see whether higher unemployment rate periods are independent from the higher crime rates regimes or not[7].

In the following section the unemployment rate will be considered as the

[7] It should be mentioned that there is no agreement about the definition of synchronized cycles.

reference variable and its cycles as the reference cycle. These cycles will be compared with cycles of the crime time series to test for common cycles. For this purpose, Concordance Index (CI), proposed originally by Harding and Pagan (2002), a method proposed by Bodman and Crosby (2005), and Pearson's contingency coefficient will be used.

The CI is a non-parametric statistic that shows the proportion of time that two series are in the same regime. For two series x_t and y_t for $t = 1, 2, ..., T$, let $S_{xt}(S_{yt})$ be a dummy variable that takes the value of unity when $x_t(y_t)$ is in regime one and value of zero when it is not in regime one. Then the CI for x_t and y_t is given by the following expression

$$CI = T^{-1}\{\sum_{t=1}^{T} S_{x_t}S_{y_t} + \sum_{t=1}^{T}(1 - S_{x_t})(1 - S_{y_t})\}.$$

For example, a value of 0.8 for this index means that two series of x_t and y_t are in the same regime 80 percent of the time. Since CI is defined as the proportion of time that two series are in the same state, this index is bounded between zero and unity. The CI index has a value of unity when $S_{x_t} = S_{y_t}$ and value of zero when $S_{y_t} = (1-S_{x_t})$. These two series are called pro-cyclical if $CI = 1$. They are counter cyclical if $CI = 0$.

It is natural to say that having a high concordance index means high common cycle. However, the question is how high should it be to interpret that as pro-cyclical? Even for two unrelated series, the expected value of the concordance index may be 0.5 or higher[8].

The above formula for concordance index can be written in a different way as follows

$$\begin{aligned} CI &= 1 + 2T^{-1}\sum_{t=1}^{T} S_{x_t}S_{y_t} - \mu_{S_x} - \mu_{S_y} \\ &= 1 + 2\rho_S\sigma_{S_x}\sigma_{S_y} + 2\mu_{S_x}\mu_{S_y} - \mu_{S_x} - \mu_{S_y}, \end{aligned}$$

where ρ_S is the estimated correlation coefficient between S_{x_t} and S_{y_t}. If $S_{x_t} = S_{y_t}$ or $S_{y_t} = (1 - S_{x_t})$, then $\sigma_{S_x}\sigma_{S_y} = \sigma^2_{S_x}$ so the value of unity for this index corresponds to $\rho_S = 1$ and value of zero to $\rho_S = 0$. Therefore,

[8] For example, consider tossing two fair coins, the probability that both coins are in the same state (either heads or tails) is 0.5.

$\rho_S = 1 (\rho_S = -1)$ shows that two cycles are perfectly positively (negatively) synchronized, and they are unsynchronized when $\rho_S = 0$.

Assuming that the two series are statistically independent ($\rho_S = 0$), the expected value of this index will be:

$$E(CI) = 1 + 2\mu_{S_x}\mu_{S_y} - \mu_{S_x} - \mu_{S_y}.$$

The expected value of being at each regime can be measured by dividing the number of periods at that regime by T. Now, this expected value can be compared with the calculated value from the series. If the former is smaller than the latter, one can say that there is a link between the cycles. This says that the number of periods where the series are in the same state is higher than if they were independent from each other. If the former is larger than the latter, one can conclude that these series are counter-cyclical. The significance of this result has to be checked, though, to see whether the ratio of these two is statistically different from 1 or not.

Another problem that exists with using this index is that it depends on the expected values of S_{x_t} and S_{y_t}, that is their mean. Suppose that the mean of S_{x_t} and S_{y_t} is 0.5 and these two series are unsynchronized, then the expected value of the concordance index will be 0.5 which confirms the assumption that they were unrelated. But if the regime that takes value of one has higher duration than the other, the mean values of the series will be higher than 0.5. Now, assume that the means are 0.8, therefore, the expected concordance index will be 0.68 which is higher than 0.5, and one may think that these two series have common cycle even though they are not related. Therefore, the mean value of the series has to taken into account by introducing the mean $\underline{\textit{corrected}}$ concordance index.

Let $\overline{S}_x = T^{-1}\sum_{t=1}^{T} S_{x_t}$ indicates the estimated probability of being at regime 1. Then the mean corrected concordance index will be

$$CI^{corr} = 2T^{-1}\sum_{t=1}^{T}(S_{x_t} - \overline{S}_x)(S_{y_t} - \overline{S}_y).$$

As mentioned before, one of the shortcomings of the concordance index is that it does not allow for a statistical testing of the result. Harding and

Pagan (2002) suggested that one can use a regression model to deal with this problem. To do so, the following regression can be used

$$\sigma_{s_y}^{-1} S_{y_t} = \alpha_1 + \rho_S \sigma_{S_x}^{-1} S_{x_t} + u_t.$$

Now, the hypothesis that $\rho_S = 0$ can be tested using the t-ratio of the coefficient of the $\sigma_{S_x}^{-1} S_{x_t}$. In this regression, when the null hypothesis is true, the error term inherits the serial correlation properties of S_{y_t}. In addition, S_{y_t} is strongly serially correlated, so the robust estimated standard errors have to be used. Using the HAC Newey-West method in estimating the model is one of the ways that one can use to take care of serial correlation and heteroscedasticity in error terms.

Using the regime classifications based on the MS models the calculated CIs are less than the expected CIs (under assumption that the series are independent) except for robbery. Also the estimated correlation between the unemployment rate and burglary, larceny, motor-vehicle theft is negative; however, it is positive between the unemployment rate and robbery. Therefore they show that the relationship between the unemployment rate and burglary, larceny and motor-vehicle theft is counter-cyclical. However, this relationship is pro-cyclical between the unemployment rate and robbery. But these results have to be tested to see whether they are statistically significant or not. According to the robust t-ratios reported at Table 3, only the results for larceny and robbery are statistically significant at 5%; so only two of the crime variables are significantly contemporaneously concordant to the unemployment rate cycle.

Therefore, it could be said that there is not any contemporaneous relationship between the unemployment rate and the following crimes: burglary and motor-vehicle theft. There is a negative and a positive contemporaneous relationship between the unemployment rate and larceny, and robbery, respectively.

The previous results were based on the assumption that the relationship between crimes and the unemployment rate, if there is any, is contemporaneous. However, maybe there is some lag between their concordances. Therefore, at this part the concordance index of the unemployment rate and crime variables with different lags is investigated. Assuming that changes in the regime of the unemployment rate at time t may cause change at the regime of the crime series at time $t+i$, where i shows the number of lagged periods.

The results are the same for the relationship between the unemployment rate, burglary, motor-vehicle theft, and robbery. However, it changes for larceny. The new results show that the correlation between the unemployment rate with one quarter lag and larceny is the same as before (negative and statistically significant at 10%) while it is not significant with two and three lags. With introducing higher lags the results change, the unemployment rate with four and five quarters lag show a positive and significant correlation with larceny. This is the case even with higher lags of the unemployment rate. Therefore, there is a positive relationship between larceny at time t with past values of the unemployment rate.

Another method used to test for any similarity or dissimilarity between the cycles of unemployment and the crime variables is the method proposed by Bodman and Crosby (2005). They used a simple but intuitive statistical method. Assume that the probability of being at regime 1 (lower regime) for the unemployment rate and robbery is 10%. Therefore, they will be in regime 1 jointly only with 1% probability if they are independent from each other.

Hence, define a dummy variable S_x to be 1 when the series is in regime one and 0 otherwise, and take these as the realization of independent Bernoulli trials with length T (sample size). Now assume that the probability of being at regime 1 is p_i for each time series. Under the null hypothesis of independence, the expected number of periods that two series jointly spend in regime 1 will be $p_i \times p_j \times T$, with a standard deviation equal to $[(p_i p_j \times (1-p_i p_j)]^{1/2}$.

Using the Markov Switching regime classification from the previous part of the paper, dummy variables are defined for being at lower regime for each time series. None of the results are statistically significant even at 10% of significance level. Therefore, based on this method the unemployment rate and all the crime variables under study are independent, and there is no significant relationship between the unemployment rate and crimes.

The conventional contingency table statistics, so called Pearson's contingency coefficient can be used to test for any form of relationship between the unemployment rate and the crime. The classification of the regimes for each single variable from the MS models can be used to create the contingency table as following

		Variable y		
		Regime 1	Regime 2	Subtotal
Variable x	Regime 1	n_{11}	n_{12}	$n_{1.}$
	Regime 2	n_{21}	n_{22}	$n_{2.}$
	Subtotal	$n_{.1}$	$n_{.2}$	N

This table can be used to check for any association between the unemployment rate and the crimes. Pearson's contingency coefficient is defined by

$$CC = \sqrt{\frac{\widehat{\chi}^2}{N + \widehat{\chi}^2}},$$

where

$$\widehat{\chi}^2 = \sum_{i=1}^{2} \sum_{j=1}^{2} \frac{[n_{ij} - (n_i.n_{.j}/N)]^2}{n_i.n_{.j}/N},$$

and n_{ij} is the number of the periods where variables x_t and y_t are respectively at regime i and j, at the same time. This coefficient is associated to the conventional correlation coefficient for continuous data. For finite dimensions, a corrected version of that has to be used. In these cases, the coefficient is bounded above and is biased from its true value. The limit of this coefficient is proportional to the dimension of the table. For a 2×2 table, the correction factor is $\sqrt{0.5}$, so the corrected contingency coefficient will have the following form

$$CC^{corr} = \frac{CC}{\sqrt{0.5}}.$$

The CC^{corr} ranges between 0 and 1. The value of 0 denotes that two series are independent, and value of unity shows a complete dependence. Larceny and robbery have the highest correlation of 0.396 and 0.349, respectively. Assuming 0.5 as the threshold level, none of the crime series shows any kind of commonality with the unemployment rate.

6 Empirical Results of MSVAR Models

In this section, bivariate MS models are estimated to investigate the common regime changes of the unemployment rate and each one of the crimes series under investigation.

The optimal number of lags of each time series have been selected using AIC and SIC criteria for the system. The selected lag for larceny and robbery is two. For burglary and motor-vehicle theft, the information criteria select, respectively, two and three lags. Because we are interested to see whether the unemployment rate has a different effect on crime in separate regimes , therefore, only models that allow for regime-dependent autoregressive parameter are estimated.

The MSIA and MSIAH models are estimated for each system using the selected optimal lags assuming two and three regimes. To choose the best MS-VAR model for each system AIC, SIC, HQ criteria, and LR (likelihood Ratio) test are used.

The selected model for the system containing burglary and the unemployment rate is a MSIAH(2)-VAR(3) model, with a very strong rejection of the null hypothesis of linearity.

The estimation results of this model are summarized in Table 7. In this model the intercept of both regimes are positive, however, it is statistically significant only at the second regime. Hence, the second regime stands for the periods with positive changes in the rate of burglary and the first regime shows the periods with no significant changes at this rate.

The estimated coefficients of lagged values of the unemployment rate in equation for burglary are significant at regime 2. However, in regime 1 only the unemployment rate with three lags is significant. The overall effect of the unemployment on burglary at regime 1 is -1.7 and at regime two is -3.5. Therefore, these results show that the unemployment rate has a negative effect on burglary regardless of the regime.

The expected duration of the regime 1 is about two years. In addition, the estimated expected durations of regimes in this model show that the period with positive changes at the rate of burglary (regime 2) lasts much less than the periods with no changes at this rate. According to the results, only

17 quarters (15%) of the 111 quarters included in this study are categorized in the second regime (higher rates of burglary). At the rest of sample period, this variable was statistically constant. The transition probabilities for these regimes show that only the first regime is persistent. The probabilities of moving from/to the first regime are different. Moving from regime two to regime one is more likely than the opposite.

Based on the smoothed and the filtered probabilities for each regime at this model for burglary, which is illustrated at Figure 6, all the periods classified as regime 2 are peaks except from the last quarter in 1981 to last quarter in 1982 and the third and fourth quarters of 1984. From the first quarter in 1985 to the end of sample, except for three quarters, all are in regime 1.

The selected model for larceny and unemployment rates is a MSIA(3)-VAR(2). The Table 8 shows the estimated results. The estimates for larceny show that the intercept of regime 1 is significant and negative and the intercept of the regime 2 is positive and significant at border of 10%, however, the other intercept is not significant. Therefore, the regimes 1, 2, and 3 stand for negative, positive, and no significant changes in larceny.

At equation for larceny, except for larceny with one lag and the unemployment rate with two lags at regime 3 the other lagged variables are not significant at conventional levels of significance. The coefficient of the unemployment rate with one lag at regime 3 is significant at the border of 10%. Therefore, the overall effect of the unemployment rate is significant only at regime 3 and it is equal to 0.76.

The transition probability matrix shows that all the regimes are persistent but the persistency of the second and third regimes are higher than the regime 1 (lower rate of larceny). Regime 3 never changes to regime 1 and it moves to regime 2 only with a 14.1% probability. The chance of having a regime with lower (constant) rate of larceny after a regime with higher rate is only 5.2% (1.4%). The expected duration of the regimes indicate that the regime 2 has the highest expected duration and regime 1 the lowest. The duration of the regime 2 and 3 is about 15 and 7 quarters, respectively.

The Figure 8 shows the smoothed and the filtered probabilities of being at each regime. For 1980:4-1982:4, 1990:3-1992:1, 2004:3-2004:4, the rate of larceny remains constant and this variable is in regime 3. The second regime, which is for high rates of larceny, consists of 1977:4, 1983:1-1983:2, 1984:2-1990:2, 1992:2-2001:2, and 2002:1-2004:1. The rest of the sample is in regime 1 and the rate of larceny at these periods is low.

The selected MS model for motor-vehicle theft and unemployment rates is a MSIA(3)-VAR(3). The estimation result of this model is reported in Table 9. The intercept of the regime 3 is -0.816 and this is the only significant intercept in all regimes. At the equation for motor-vehicle theft, in regime 1 (3) only the coefficient of the unemployment rate with three (two and three) periods lag is significant. In regime 2 the lagged unemployment rates are not significant at conventional levels of significance. The overall effect of the unemployment rate in regime 1 and 3 is -0.044 and 0.166, respectively. Therefore, the unemployment rate has different effect in separate regimes.

At the same time, regime 1 has the highest duration and lasts more than 6 years; in addition, regime 3 lasts less than half a year. Regime 1, 2, and 3 includes 58.3, 34.1, and 18.5 quarters of the sample. Furthermore, regime 1 is very persistent with a probability equal to 96.2%, regime 2 is persistent as well but the last regime is not persistent. Regime 2 never changes to regime 1 and it changes to regime 3 with probability of 37.7%. At the same time regime 1 never alter to regime 3.

Classification of the regimes is illustrated in Figure 9. Based on the estimated smoothed probabilities for each regime, regime 1 consists of 1978:1979:4, 1991:1-2000:4, and 2002:1-2004:4. The rest of the sample are peaks that oscillate between regime 2 or 3.

The information criteria and the LR test select a MSIA(2)-VAR(2) model for the variables robbery and unemployment rates. This model has 2 regimes and intercept and autoregressive parameters are regime dependent. The estimated results are presented in Table 10.

The results show that both of the intercepts are positive, however it is significant only at regime 2. Therefore, it could be said that regime 1 shows a regime with constant rate of robbery and regime 2 stands for higher rates of robbery. The estimated coefficients of lagged values of robbery and the unemployment rate are not significant at none of the regimes. Consequently, the unemployment rate does not have any significant effect on the rate of robbery.

The transition probabilities show that both regime 1 and 2 are very persistent. There is only a 1.2% chance of moving from regime 1 to regime 2 and the probability of moving in opposite direction is 10.3%. Out of 111 observation included in this study 98.9 quarters are in regime 1 and only 12.1 quarters in regime 2. The duration of the first regime is also much higher than the second regime. The estimated smoothed probabilities at fig.(11) show that regime 2 begins from the first quarter in 1980 and stops at the end of 1982. The rest of the sample is in regime1.

7 Conclusions

The results of univariate MS-AR models jointly with different measures have been used to test the existence of any relationships between the unemployment rate and the crime variables. The results confirm that there is no relationship between the unemployment rate, burglary and motor-vehicle theft. The results for larceny and robbery are mixed. The CI is the only measure that shows a relationship between the unemployment rate and robbery and larceny. The contemporaneous relationship is positive for robbery and negative for larceny, however, it turns to be positive between the lagged values of the unemployment rate and larceny.

The objective of second phase, MS-VAR models, was to test for the existence of different influences of the unemployment rate in separate states of the crime. Therefore, the overall effects of the unemployment rate in different regimes on the crime series are estimated. The results are mixed. The results show that the unemployment rate has a negative effect on burglary regardless of the state of the burglary rate, and it does not have any significant effect on robbery during the periods under study. As for the larceny and motor-vehicle theft, the effect of the unemployment rate depends on the regime of these variables. For larceny and motor-vehicle theft this effect is positive and zero in regime 3 and 2, respectively. At regime 1 for these crimes, the overall effect of the unemployment rate on larceny is zero; however, it is negative for motor-vehicle theft.

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Table 1. Results of Univariate MS-AR models for Crimes

	Burglary		Robbery	Larceny	Motor
	MSIH(2)-AR(1)	MSIH(3)-AR(8)	MSIH(2)-AR(1)	MSI(2)-AR(1)	MSI(2)-AR(1)
			Intercepts		
μ_1	-6.049 (-1.571)	-5.797 (-1.517)	-3.289 (-1.270)	-2.773 (-4.098)	-0106 (-1.032)
μ_2	0.677 (0.481)	-8.397 (-49.224)	-1.478 (-0.319)	2.106 (5.729)	0.197 (2.001)
μ_3		2.983 (2.561)			
			Autoregressive Parameters		
ϕ_1	0.061 (0.511)	-0.047 (-6.623)	-0.015 (-0.194)	0.094 (1.038)	-0.104 (-0.923)
ϕ_2		-0.027 (-2.911)			
ϕ_3		0.069 (10.958)			
ϕ_4		-0.052 (-6.797)			
ϕ_5		0.107 (18.192)			
ϕ_6		0.109 (17.025)			
ϕ_7		0.196 (27.136)			
ϕ_8		-0.126 (-17.474)			
Dummy 1			98.852 (5.370)	-10.989(-4.971)	
Dummy 2			-97.897 (-6.482)		
			Standard Errors		
σ_1	22.605	21.369	13.359	2.172	0.301
σ_2	9.464	0.334	27.824		
σ_3		8.501			
			Transition Probabilities		
p11	0.902	0.745	0.889	0.658	0.959
p12	0.098	0.253	0.111	0.342	0.041
p13		0.002			
p21	0.04	0.369	0.147	0.082	0.076
p22	0.96	0.347	0.853	0.918	0.924
p23		0.285			
p31		0.058			
p32		0			
p33		0.942			
			Durations		
Regime 1	10.18	3.93	9.01	2.93	24.33
Regime 2	24.73	1.53	6.8	12.17	13.2
Regime 3		17.12			
			Log Likelihood		
Nonlinear	-450.05	-421.027	-490.75	-268.123	-31.197
Linear	-461.335	-452.363	-495.241	-273.131	-34.740

t-statistics are in paranthesis.

Table 2. Results of MSIAH(2)–AR(3) for Unemployment

	Regime 1	Regime 2
μ	0.139 (1.085)	0.607 (2.271)
ϕ_1	1.189 (9.757)	1.613 (8.630)
ϕ_2	-0.056 (-0.302)	-0.730 (-2.221)
ϕ_3	-0.166 (-1.500)	0.036 (0.192)
Standard errors	0.119	0.285
Duration	16.48	6.14
	Log Likelihood	
Nonlinear	37.311	
Linear	19.840	

Transition Probabilities

	Regime 1	Regime 2
Regime 1	0.939	0.061
Regime 2	0.163	0.837

t-statistics are in parenthesis.

Table 3. Calculated results of Concordance Index

	Unemployment rate & Burglary 2 regimes	Unemployment rate & Burglary 3 regimes	Unemployment rate & Larceny	Unemployment rate & Motor	Unemployment rate & Robbery
CI	0.333	0.288	0.261	0.55	0.667
E(CI)	0.414	0.349	0.361	0.551	0.555
$\hat{\rho}$	-0.195	-0.192	-0.292	-0.004	0.255
t-ratio	-1.196	-1.473	-2.212	-0.027	1.643
CI^{corr}	-0.081	-0.061	-0.1	-0.002	0.111

Table 4. The Estimated Correlations between Crime Variables and Unemployment rate;
From regressing crime variables on lagged values of unemployment rate.

	Unemployment rate& Burglary 2 regimes	Unemployment rate& Burglary 3 regimes	Unemployment rate& Larceny	Unemployment rate& Motor	Unemployment rate& Robbery
1 lag	-0.161	-0.076	-0.305*	0.003	0.305*
t-ratio	-0.932	-0.639	-1.851	0.017	1.875
2 lag	-0.171	-0.131	-0.213	0.011	0.355*
t-ratio	-0.983	-1.213	-1.552	0.062	2.337
3 lag	-0.137	-0.089	-0.067	0.018	0.406*
t-ratio	-0.834	-0.759	-0.666	0.107	2.699
4 lag	-0.103	-0.087	0.133*	-0.015	0.416*
t-ratio	-0.658	-0.753	1.853	-0.088	2.676
5 lag	-0.069	-0.085	0.244*	-0.02	0.384*
t-ratio	-0.455	-0.706	2.809	-0.108	2.373
6 lag	-0.034	-0.141	0.247	0.018	0.352*
t-ratio	-0.231	-1.308		0.096	2.206
7 lag	0	-0.139	0.251	0.055	0.277*
t-ratio	0	-1.091		0.303	1.74
8 lag	0.034	-0.078	0.254*	0.093	0.245
t-ratio	0.22	-0.689	2.998	0.511	1.603

* indicate the significant correlations at 10% or lower.

Table 5.Calculate CIs between Crime Variables and Lagged Values of The unemployment Rate

	Unemployment rate& Burglary 2 regimes	Unemployment rate& Burglary 3 regimes	Unemployment rate& Larceny	Unemployment rate& Motor	Unemployment rate& Robbery
1 lag	0.342	0.324	0.252	0.55	0.685
2 lag	0.333	0.306	0.279	0.55	0.703
3 lag	0.342	0.315	0.324	0.55	0.721
4 lag	0.351	0.315	0.387	0.532	0.721
5 lag	0.36	0.315	0.423	0.523	0.703
6 lag	0.369	0.297	0.423	0.532	0.685
7 lag	0.378	0.297	0.423	0.541	0.649
8 lag	0.387	0.315	0.423	0.55	0.631

Table 6. Results from Bodman and Crosby Method

	Unemployment rate & Burglary 2 regimes	Unemployment rate & Burglary 3 regimes	Unemployment rate & Larceny	Unemployment rate & Motor	Unemployment rate & Robbery
Actual number of quarters jointly at regime 1	19	8	8	49	56
Number of quarters at regime 1 assuming independency	23.486	11.387	13.523	49.108	49.82
Standard deviation	4.303	3.197	3.446	5.233	5.24

Table 7. Estimation Results MSIAH(2)-VAR(3)Model of Burglary

	Regime 1		Regime 2	
	Dburglary	unemployment	Dburglary	unemployment
μ	7.415(1.209)	0.351(5.159)	30.554(2.448)	0.229(0.402)
$\phi_{1,1}$	0.236(2.500)	-0.003(-3.222)	-1.007(-10.788)	0.008(1.722)
$\phi_{1,2}$	-0.120(-1.405)	-0.002(-2.449)	0.531(3.881)	-0.004(-0.596)
$\phi_{1,3}$	0.190(2.248)	-0.001(-1.129)	-0.394(-3.889)	-0.005(-1.029)
$\phi_{2,1}$	-6.303(-0.847)	1.230(14.891)	-40.687(-6.496)	1.688(5.471)
$\phi_{2,2}$	19.352(1.525)	-0.137(-0.958)	71.390(7.299)	-0.801(-1.664)
$\phi_{2,3}$	-14.749(-2.038)	-0.160(-1.935)	-34.240(-6.721)	0.100(0.399)
σ	12.018	0.131	5.582	0.275
		Log Likelihood		
Nonlinear		-391.945		
Linear		-432.636		

t-statistics are in parenthesis.

Transition Probabilities

	Regime 1	Regime 2	Duration
Regime 1	0.875	0.125	8.03
Regime 2	0.695	0.306	1.44

Table 8. Estimation Results MSIA(3)-VAR(2)Model of Larceny

	Regime 1		Regime 2		Regime 3	
	Dlarceny	unemployment	Dlarceny	unemployment	Dlarceny	unemployment
μ	-12.420(-3.598)	0.828(4.271)	2.199(1.641)	0.189(2.539)	-2.846(-0.723)	0.099(0.486)
$\phi_{1,1}$	-0.384(-1.548)	-0.049(-4.129)	0.147(1.311)	-0.003(-0.648)	0.645(3.528)	0.051(5.524)
$\phi_{1,2}$	-0.039(-0.097)	0.113(4.188)	0.054(0.570)	0.007(1.508)	-0.104(-0.533)	0.020(1.991)
$\phi_{2,1}$	-1.262(-0.408)	1.861(9.803)	-1.566(-0.904)	1.020(12.491)	-4.405(-1.624)	1.034(7.039)
$\phi_{2,2}$	2.630(0.904)	-0.972(-5.795)	1.402(0.795)	-0.247(-2.474)	5.175(1.760)	-0.022(-0.140)
D2003	-2.621(-0.151)	0.236(0.267)	-10.342(-4.455)	0.335(2.829)	-11.891(-0.282)	-0.036(-0.017)
σ	2.266	0.116	2.266	0.116	2.266	0.116
			Log Likelihood			
Nonlinear			-199.93			
Linear			-249.36			

t-statistics are in parenthesis.

Transition Probabilities

	Regime 1	Regime 2	Regime 3	Duration
Regime 1	0.555	0.297	0.149	2.25
Regime 2	0.052	0.934	0.014	15.23
Regime 3	0	0.141	0.859	7.11

Table 9. Estimation Results MSIA(3)-VAR(3)Model of Motor

	Regime 1		Regime 2		Regime 3	
	Dmotor	unemployment	Dmotor	unemployment	Dmotor	unemployment
μ	0.148(0.733)	0.079(0.609)	-0.050(-0.235)	0.727(5.637)	-0.816(-2.100)	1.493(5.444)
$\phi_{1,1}$	-0.165(-1.576)	-0.058(-0.900)	-0.246(-1.982)	-0.092(-1.382)	1.028(3.481)	-0.953(-4.871)
$\phi_{1,2}$	-0.207(-2.028)	-0.117(-1.886)	0.416(3.336)	-0.138(-1.999)	-0.882(-4.285)	-0.150(-1.160)
$\phi_{1,3}$	-0.107(-1.051)	-0.005(-0.075)	0.401(3.790)	-0.094(-1.472)	-0.155(-0.761)	-0.194(-1.466)
$\phi_{2,1}$	0.297(1.538)	1.221(10.303)	0.248(1.458)	1.203(10.783)	0.231(0.725)	1.148(5.001)
$\phi_{2,2}$	0.078(0.238)	0.069(0.351)	-0.414(-1.514)	-0.352(-2.008)	-1.489(-2.447)	0.499(1.144)
$\phi_{2,3}$	-0.419(-2.203)	-0.312(-2.724)	0.184(1.131)	0.033(0.355)	1.424(4.080)	-0.832(-3.360)
σ	0.215	0.131	0.215	0.131	0.215	0.131
			Log Likelihood			
Nonlinear			39.614			
Linear			-8.384			

t-statistics are in parenthesis.

Transition Probabilities

	Regime 1	Regime 2	Regime 3	Duration
Regime 1	0.962	0.038	0	26.56
Regime 2	0	0.623	0.377	2.66
Regime 3	0.163	0.552	0.285	1.4

Table 10. Estimation Results MSIA(2)-VAR(2)Model of Robbery

	Regime 1		Regime 2	
	Drobbery	unemployment	Drobbery	unemployment
μ	10.044(1.078)	0.326(4.508)	117.856(2.697)	0.438(1.399)
$\phi_{1,1}$	-0.078(-0.988)	0.001(2.308)	-0.032(-0.131)	0.002(0.882)
$\phi_{1,2}$	0.096(1.176)	0.000(0.145)	-0.244(-1.109)	-0.011(-6.434)
$\phi_{1,1}$	5.770(0.581)	1.386(17.868)	5.625(0.330)	1.436(10.632)
$\phi_{1,2}$	-8.104(-0.847)	-0.448(-5.990)	-20.919(-1.128)	-0.456(-3.119)
D1993	102.968(5.249)	-0.073(-0.481)	77.160(338.796)	-0.752(-0.204)
D1994	-100.258(-5.124)	0.092(0.606)	-117.797(-2411.194)	0.041(0.010)
σ	19.2	0.149	19.2	0.149
		Log Likelihood		
Nonlinear		-439.875		
Linear		-464.712		

t-statistics are in parenthesis.

	Transition Probabilities		
	Regime 1	Regime 2	Duration
Regime 1	0.988	0.012	85.84
Regime 2	0.103	0.897	9.74

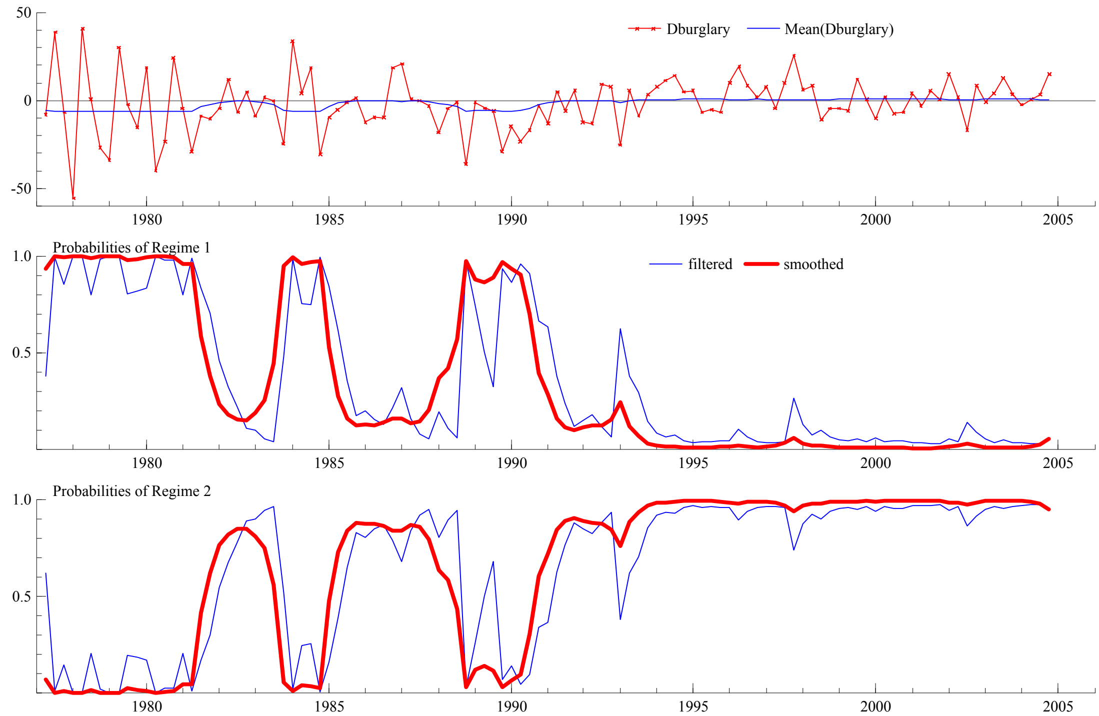

Figure 1. Mean, smoothed, and filtered probabilities of Burglary; MSIH(2)-AR(1) model

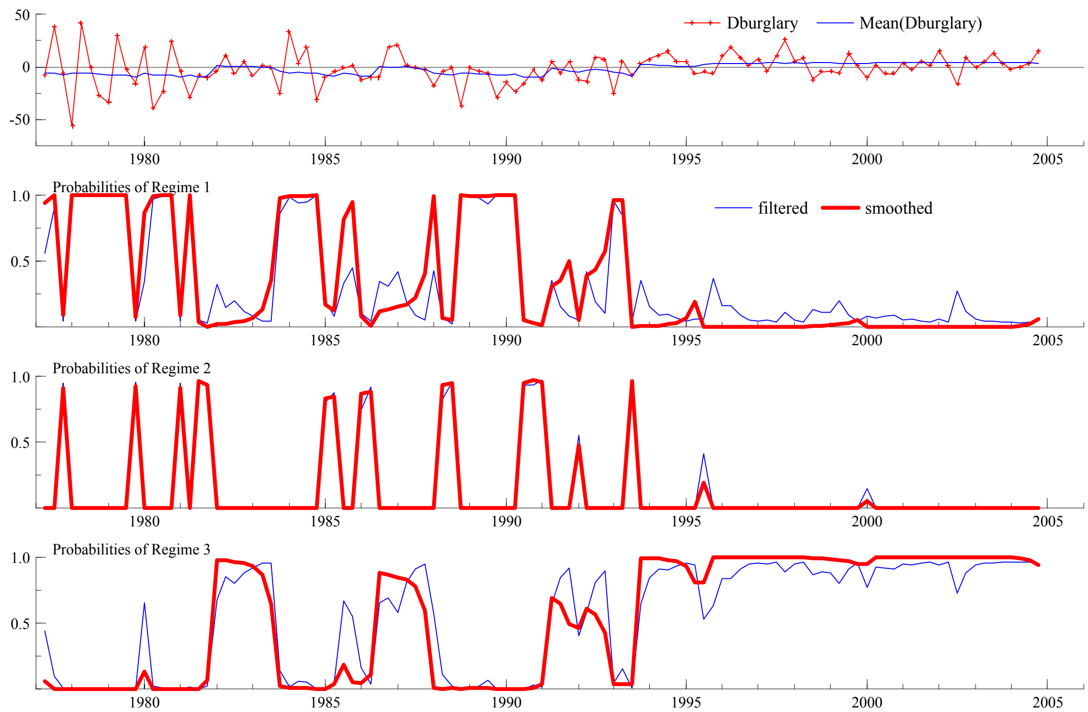

Figure 2. Mean, smoothed, and filtered probabilities of Burglary; MSIH(3)-AR(8) model

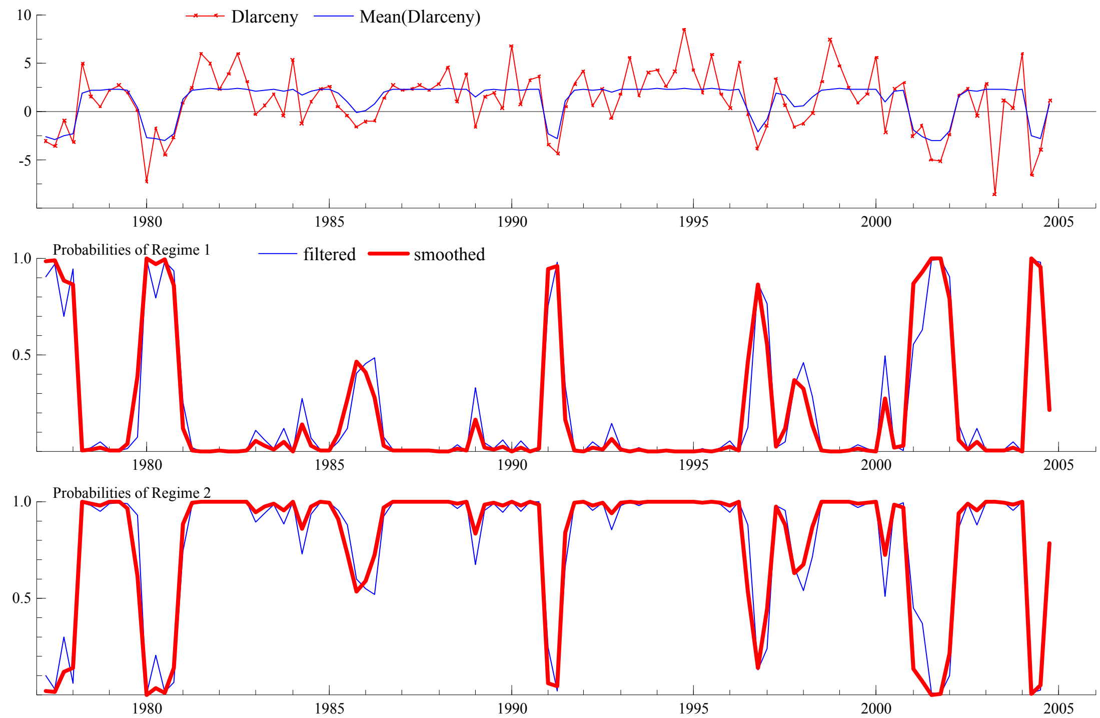

Figure 3. Mean, smoothed, and filtered probabilities of Larceny; MSI(2)-AR(1) model

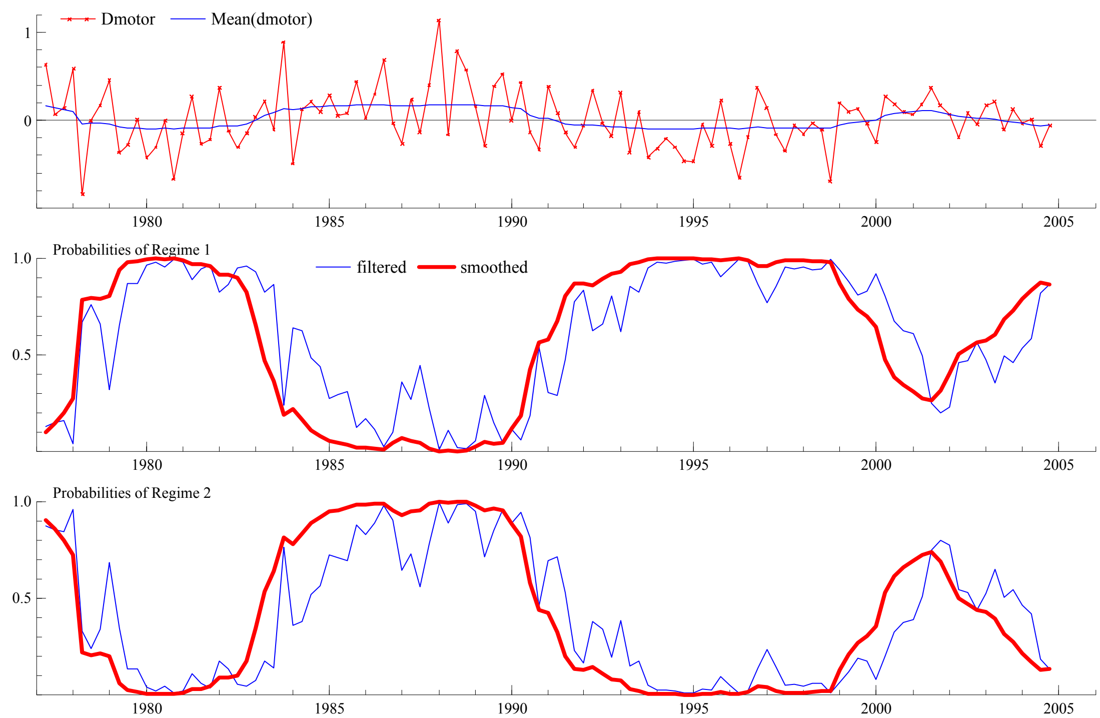

Figure 4. Mean, smoothed, and filtered probabilities of Motor; MSI(2)-AR(1) model

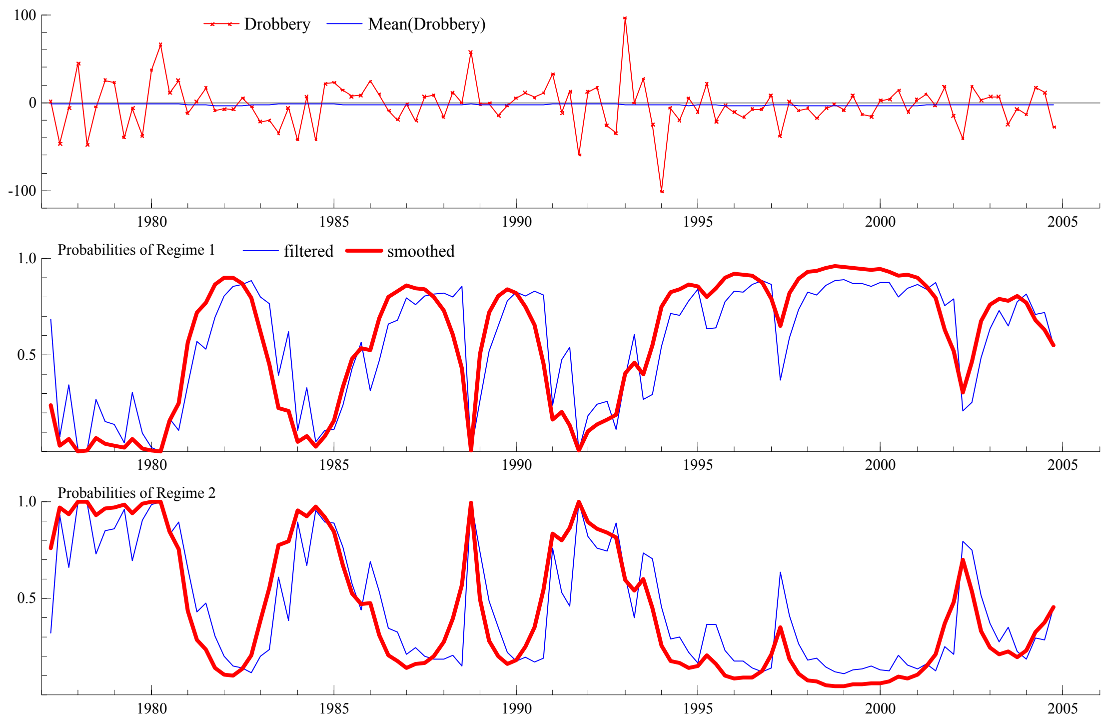

Figure 5. Mean, smoothed, and filtered probabilities of Robbery; MSIH(2)-AR(1) model

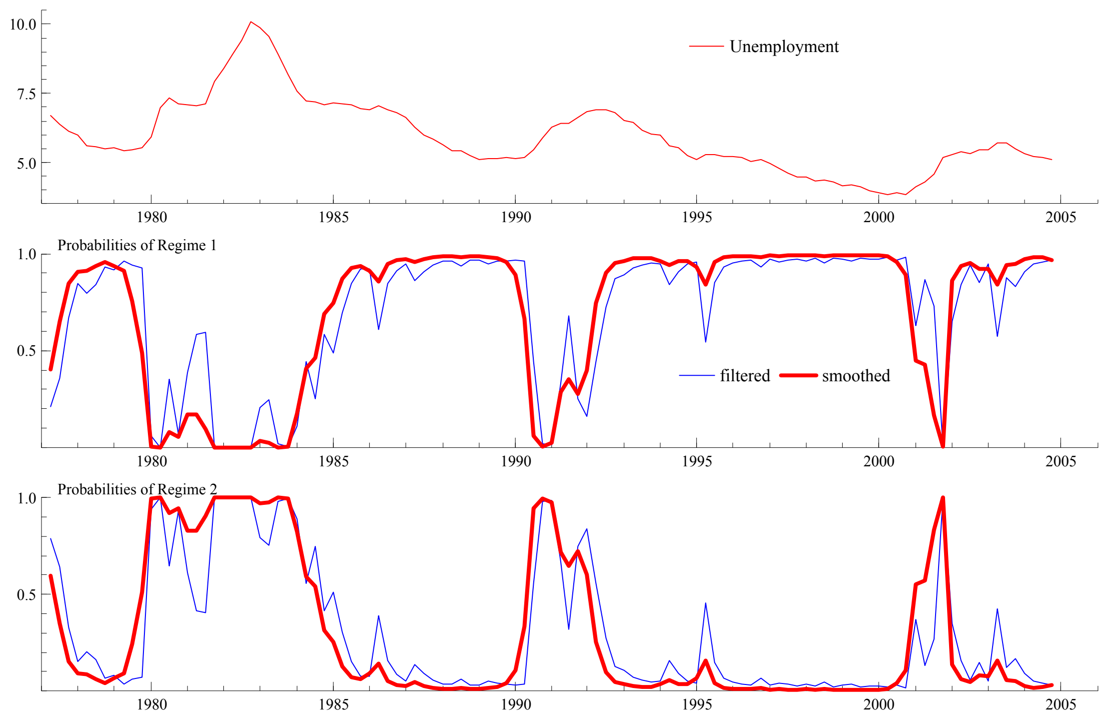

Figure 6. Mean, smoothed, and filtered probabilities of the unemployment Rate; MSIAH(2)-AR(3)

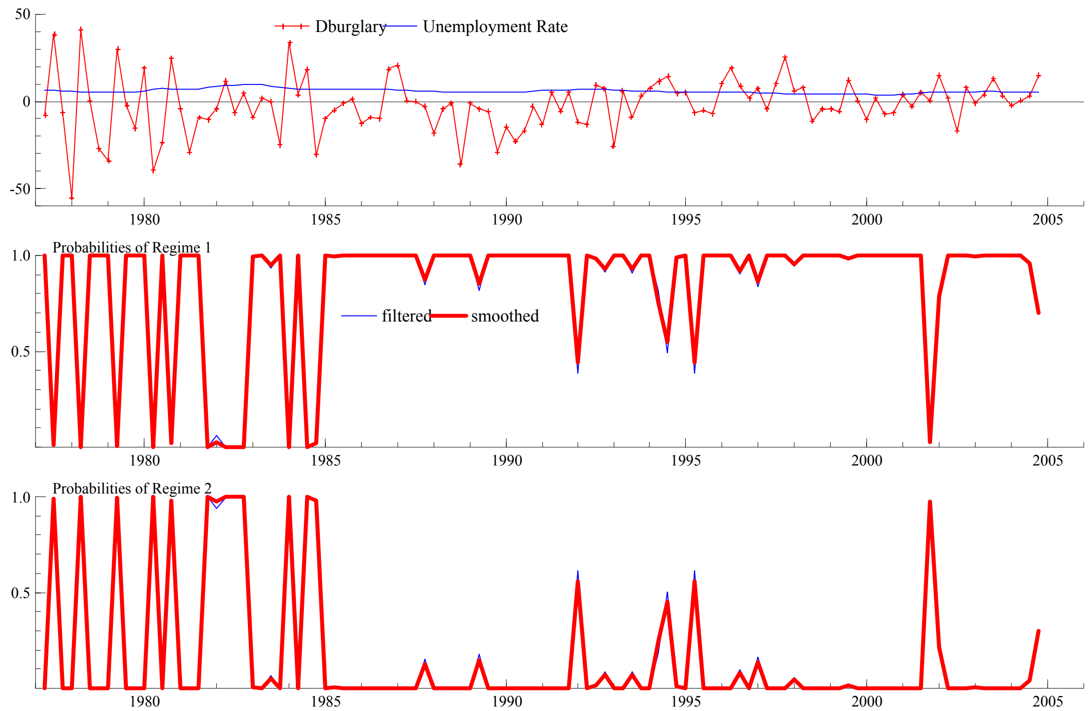

Figure 7. Series, smoothed and filtered probabilities of bivariate model for Burglary and the unemployment rate, MSIAH(2)-VAR(3)

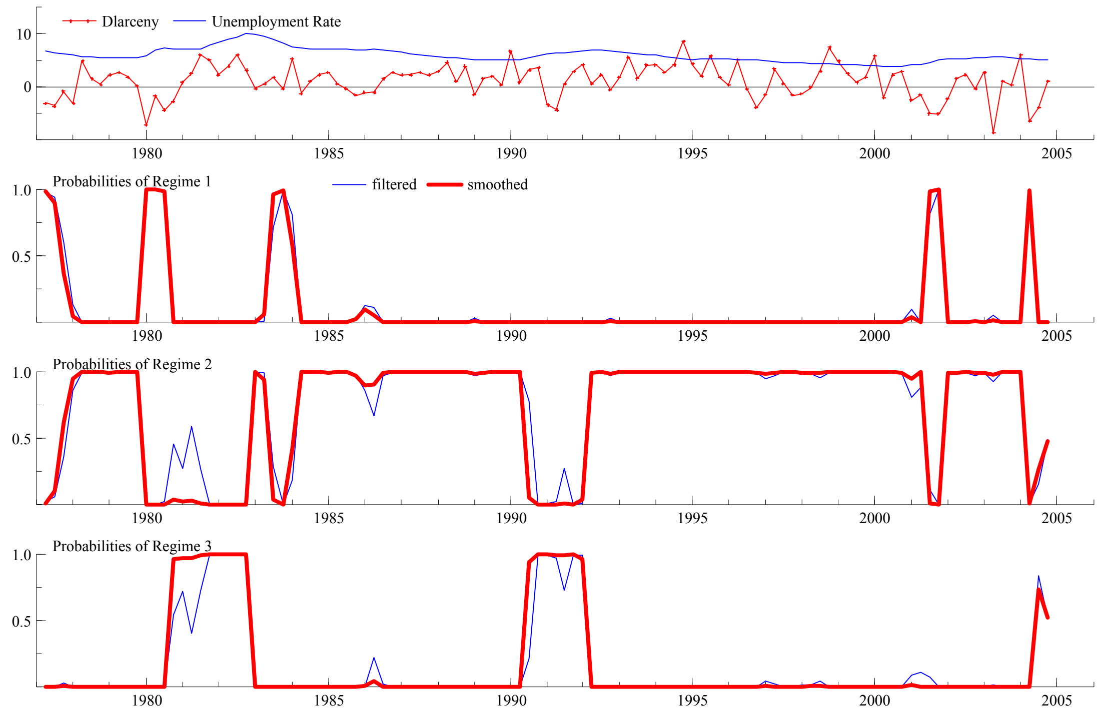

Figure 8. Series, Smoothed and Filtered Probabilities of bivariate model for Larceny and the unemployment rate, MSIA(3)-VAR(2)

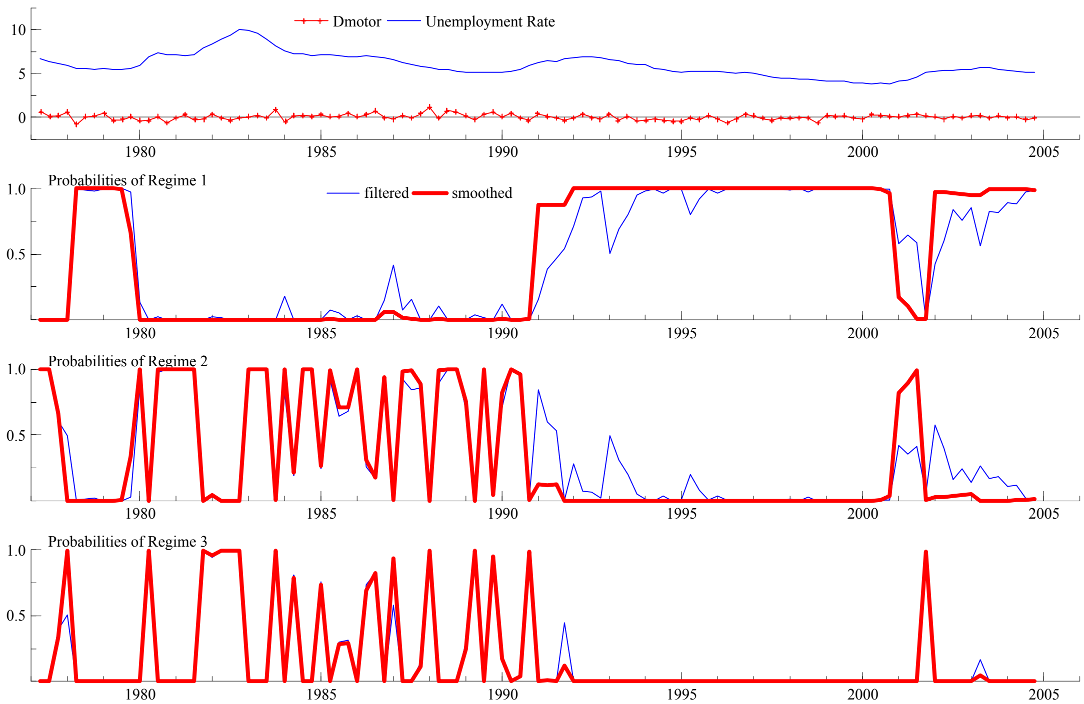

Figure 9. Series, smoothed and filtered probabilities of bivariate model for Motor and the unemployment rate, MSIA(3)-VAR(3)

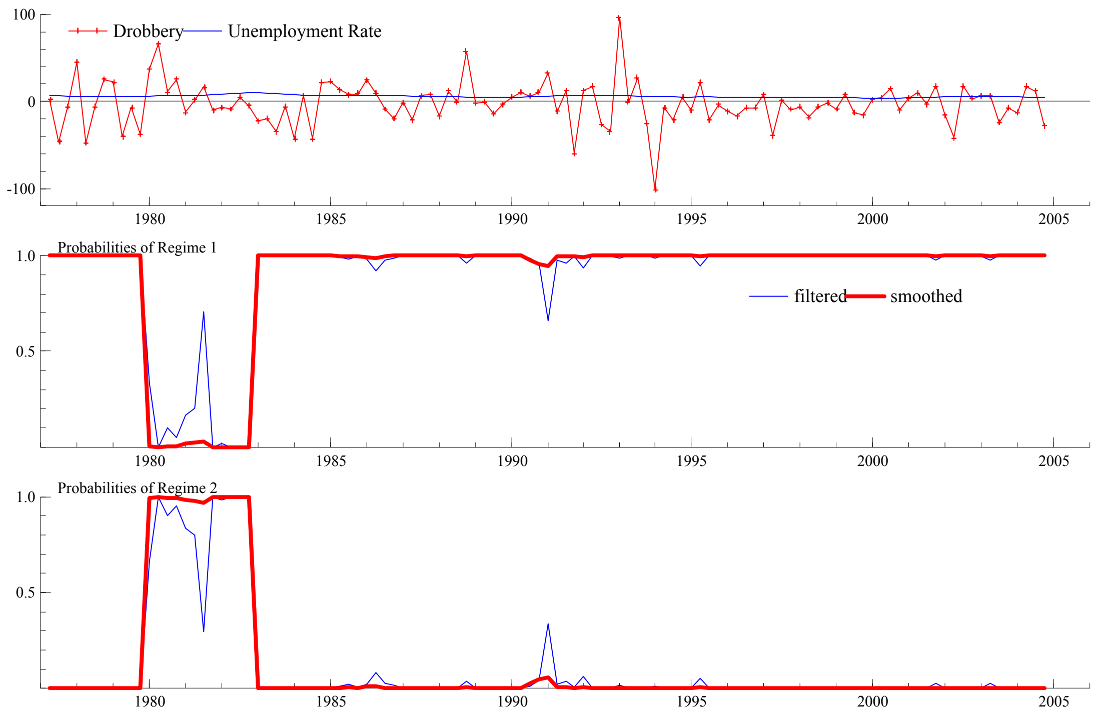

Figure 10. Series, smoothed and filtered probabilities of bivariate model for Robbery and the unemployment rate, MSIA(2)-VAR(2)