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Av. Universitaria 1801, Lima 32 – Perú.
Teléfono: (51-1) 626-2000 anexos 4950 - 4951
Fax: (51-1) 626-2874
econo@pucp.edu.pe
www.pucp.edu.pe/departamento/economia/

Encargada de la Serie: Giovanna Aguilar Andía
Departamento de Economía – Pontificia Universidad Católica del Perú,
gaguila@pucp.edu.pe

Fallahi, Firouz y Rodríguez, Gabriel

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Is There a Link between Unemployment and Criminality in the US Economy? Further Evidence

Firouz Fallahi
University of Tabriz, Iran

Gabriel Rodríguez
Pontificia Universidad Católica del Perú

Abstract

Using Markov-Switching models, this paper studies the existence of a relationship between the unemployment rate and four different types of crimes in the U.S. economy. After it, using the non-parametric Concordance Index of Harding and Pagan (2002, 2006), the correlation between the cycles of unemployment rate and crime variables is determined. Results confirm that there is no significant relationship between the unemployment rate, burglary and motor-vehicle theft. However, the unemployment rate has a significant relationship with 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.

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

JEL Classification: C22, K14

Resumen

Utilizando modelos Markov-Switching, este documento investiga la existencia de una relación entre la tasa de desempleo y cuatro diferentes tipos de criminalidad en la economía de los Estados Unidos. Asimismo, se analiza la correlación entre los ciclos de la tasa de de desempleo y las diferentes variables de criminalidad utilizando una medida no paramétrica denominada indice de concordancia propuesto por Harding y Pagan (2002, 2006). Los resultados indican que no existe una relación estadísticamente significativa entre la tasa de desempleo y las tasas de robo violentos y robo de vehículos. Sin embargo, la tasa de desempleo presenta una relación estadísticamente significativa con asaltos a mano armada y hurtos o fraudes. La relación es contemporáneamente positiva con la tasa de robo a mano armada y negativa con la tasa de hurto o fraude. Sin embargo esta relación se vuelve positiva entre valores rezagados de la tasa de hurto o fraude y la tasa de desempleo.

Palabras Claves: Modelos Markov-Switching, Ciclos, Desempleo, Criminalidad.

Classificación JEL: C22, K14

Is There a Link between Unemployment and Criminality in the US Economy? Further Evidence[1]

Firouz Fallahi
University of Tabriz

Gabriel Rodríguez[2]
Pontificia Universidad Católica del Perú

1 Introduction

Although economic theory anticipates the existence of a positive relationship between unemployment and crime, empirical works in this regard have found mixed results. Chiricos (1987) reviewed 68 studies about the relationship between crime and the unemployment rate and 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.

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 a significant relationship between unemployment and five kinds of crime. Their results also show that there is no relationship between unemployment and auto theft. Property crimes including theft, burglary, and robbery had positive relationships with changes in the unemployment rate. Robbery had negative

[1] This paper is drawn from the first chapter of the PhD dissertation of Firouz Fallahi when Gabriel Rodríguez was Associate Professor at the Department of Economcis of the University of Ottawa. We thank Lynda Khalaf, Marcel Voia, and Gamal Atallah for constructive comments.

[2] Address for Correspondence: Gabriel Rodríguez, Department of Economics, Pontificia Universidad Católica del Perú, Av. Universitaria 1801, Lima 32, Lima, Perú, Telephone: +511-626-2000 (4998), Fax: +511-626-2874. E-Mail Address: gabriel.rodriguez@pucp.edu.pe.

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 a negative effect on homicide and aggravated assault for the younger age groups and a positive effect for older age groups. Witt, Clarke and Fielding (1999) found a positive relationship between crime and the male unemployment rate.

Entorf 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 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 unemployment becomes higher and unambiguously positive.

Greenberg (2001) used time series data, cointegration, and error correction models to investigate the relationship between divorce and unemployment rates 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. Imrohoroglu 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 showed that there is a strong positive relationship between the unemployment rate, burglary, car theft and bike theft.

Recently Lee and Holoviat (2006) used the cointegration approach to identify a long run relationship between unemployment and a set of crime variables in three Asian-Pacific countries. They found 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. However, the unemployment rate is directly related to business cycles and has a cyclical pattern so linear models may provide a weak fit. Consequently, one needs to use non-linear models, such as the Markov Switching (MS) models (Hamilton, 1989). These models have the capability to capture changes in the behavior of time series by allowing the switching between regimes or states. 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 type 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 methods. 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 rate and the different crime rates in the U.S. economy. Our sampling period covers 1975:1 until 2004:4 and four types of crimes are analyzed: burglary, larceny, motor-vehicle theft, and robbery.[3]

The Markov-Switching methodology is used to investigate the behavior of the unemployment rate and crime variables. The results show that there is no relationship between the unemployment rate, burglary and motor-vehicle theft. However, the unemployment rate has a significant relationship with robbery and larceny. The contemporaneous relationship between the rate of unemployment and robbery is positive, and it is negative between the unemployment rate and larceny. However, the unemployment rate of past periods has significantly positive effect on current rate of larceny.

The remaining portion of this paper is organized as follows. Second section describes the methodology. Section 3 shows the results obtained. Section 4 deals with synchronization of cycles using the non-parametric Concordance Index of Harding and Pagan (2002), to check the relationship between the cycles of the unemployment rate and crime variables. Section 5 concludes.

2 Methodology

Let y_t denotes the variable we are interested to analyze at the quarter t. Following. Hamilton (1989) we may propose the following model for the

[3] These four types of crime cover 92% of the total crime in the U.S. in 2004.

variable y_t:

$$y_t - \mu_{s_t} = \phi_1(y_{t-1} - \mu_{s_{t-1}}) - ... - \phi_k(y_{t-k} - \mu_{s_{t-4}}) + \epsilon_t, \tag{1}$$

where s_t is an unobserved variable indicating the state of the economy, and $\epsilon_t \sim i.i.d.\ N(0, \sigma^2)$. A full description of the dynamics of y_t is obtained if we have a probabilistic description of how the economy changes from one regime to another. The simplest such model is a Markov chain, that is a model where

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

with $\sum_{j=1}^{M} p_{ij} = 1,\ \forall\ i, j \in \{1, 2, ..., M\}$. Therefore we have a matrix of transition probabilities

$$P = \begin{bmatrix} p_{11} & p_{12} & ... & p_{1M} \\ p_{21} & p_{22} & ... & p_{2M} \\ .... & .... & ... & ... \\ p_{M1} & p_{M2} & ... & P_{MM} \end{bmatrix} \tag{2}$$

with $p_{iM} = 1 - p_{i1} - p_{i2} - ... - p_{iM-1}$, for $i = 1, 2, ..., M$.

In the model (1) only the value of the mean is regime dependent. It is denoted as MSM(2)-AR(k) which denotes a Markov switching model with mean regime dependent, two regimes and an autoregression of order k. Other specifications are available. For example, a model where the mean, the variance and the autoregressive coefficients are regime dependent is denoted by MSMAH(m)-AR(k) where m indicates the number of states and k reflects the order of the autoregression. In some cases instead of modeling the mean as regime dependent parameter, it is considered the intercept as regime dependent. The model where the mean and the intercept are regime dependent are not equivalent. They imply different dynamics of adjustment of the variables after a change in regime.

The maximization of the likelihood function of an MS-AR model entails an iterative technique. This technique gives us the parameters of the autoregression and the transition probabilities governing the Markov chain of the unobserved states. Denote this parameter vector by $\lambda = (\theta, \rho)$.

Maximum likelihood estimation of the model is based on the Expectation Maximization (EM) algorithm proposed by Hamilton (1990). Each iteration of the EM algorithm consists of two steps: the *expectation* step and the *maximization* step. Calculations are simplified using the recursive and smoothing algorithms discussed in Krolzig (1997).

Once the coefficients of the model are estimated and a 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 the whole sample), the corresponding series of probabilities is known as "filtered probabilities".

3 Empirical Results of the Univariate MS-AR Models

Quarterly data of four crime 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 Gómez-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 GLS-based Augmented Dickey-Fuller (ADF^{GLS})statistic of Elliott, Rothenberg and Stock (1996), 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).

Given previous results of the unit root tests, the crime series are modeled in first differences and the unemployment rate enters in levels. A generalized version of the model suggested by Hamilton (1989) is estimated. All estimations are carried out using the MSVAR class for Ox by Krolzig (2005).

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 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 fitting MS models. The null hypothesis of linearity is rejected for all selected models.[4]

[4] Using LR test and Davis' bounded LR test. Results are available upon request.

3.1 Burglary

For this time series the MSIH(2)-AR(1) is selected as the best model and the Table 1 shows results for this model. The null hypothesis of linearity for this time series is rejected. Overall, the results show 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), respectively. 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 results show 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 presented in Figure 1. 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).

3.2 Larceny

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

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. Results show that the first regime has a negative intercept, while 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.

Figure 2 shows the smoothed and the filtered probabilities of larceny in the two regimes. According to these results, the first regime (decreasing rates of larceny) consists of 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.

3.3 Motor-Vehicle Theft

For this variable, the AIC and the LR test suggest that the best model is a MSIAH(2)-AR(1). However, 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.

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 changes 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.

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.

3.4 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.

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.

3.5 Unemployment Rate

Although the information criteria have selected the MSI(2)-AR(3) as the best model, it cannot 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.

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 1 and 2. Therefore, the regime with higher unemployment rates is more volatile than the first regime.

Regime 1 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 1 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.

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.

4 Synchronization of Cycles

So far, MS models for each single time series has been estimated and their properties, 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 relationship between the unemployment rate (as an indicator of the position 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 correlated with the higher crime rates regimes or not.

The unemployment rate will be considered as the 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 the Concordance Index (CI), proposed originally by Harding and Pagan (2002, 2006) is 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 1 and value of zero when it is not in regime 1. Then the CI for x_t and y_t is given by the following expression

$$CI = T^{-1}\{\sum_{t=1}^{T} S_{x_t} S_{y_t} + \sum_{t=1}^{T} (1 - S_{x_t})(1 - S_{y_t})\}. \tag{3}$$

For example, a value of 0.8 for this index means that two series (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.[5]

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

$$\begin{aligned} CI &= 1 + 2T^{-1} \sum_{t=1}^{T} S_{x_t} S_{y_t} - \mu_{S_x} - \mu_{S_y} \\ &= 1 + 2\rho_S \sigma_{S_x} \sigma_{S_y} + 2\mu_{S_x} \mu_{S_y} - \mu_{S_x} - \mu_{S_y}, \end{aligned} \tag{4}$$

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

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

$$E(CI) = 1 + 2\mu_{S_x} \mu_{S_y} - \mu_{S_x} - \mu_{S_y}. \tag{5}$$

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

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

says that the number of periods where the series are in the same state is higher than if they were uncorrelated. 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 be taken into account. For this purpose the mean corrected concordance index (Artis et al, 2004) is considered.

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

$$CI^{corr} = 2T^{-1}\sum_{t=1}^{T}(S_{x_t} - \overline{S}_x)(S_{y_t} - \overline{S}_y). \tag{6}$$

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

$$\sigma_{s_y}^{-1} S_{y_t} = \alpha_1 + \rho_S \sigma_{S_x}^{-1} S_{x_t} + u_t. \tag{7}$$

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 robust estimated standard errors have to be used (such as HAC Newey-West method).

Using the regime classifications based on the MS models the calculated CIs are less than the expected CIs (under the assumption that the series are uncorrelated) 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. This shows 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. 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 with the unemployment rate cycle.

In summary we find no 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. We next investigate the concordance index of the lagged values of the unemployment rate and crime variables, assuming that changes in the regimen of unemployment rate at $t - i$ may be related with changes at the regime of the crime series at time t, 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, results change for larceny: correlation between the unemployment rate with one quarter lag and larceny is the same as for the contemporaneous case (negative and statistically significant at 10%) while it is not significant with two and three lags. With introducing higher lags the results change, and the unemployment rate with four and five quarters lags 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 (see Tables 4 and 5).

5 Conclusions

Although economic theory anticipates the existence of a positive relationship between unemployment rate and crime rates, empirical works in this regard have found mixed results. For example, Chiricos (1987) reviewed 68 studies about the relationship between crime and the unemployment rate and 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.

We apply Markov-Switching models to the unemployment rate and to four types of crime. We identify recessions and expansion periods for each one of these variables. The results of these univariate MS-AR models jointly with Concordance Index have been used to test the existence of any relationships between the unemployment rate and the crime variables in the US economy. Results confirm that there is no significant relationship between the unemployment rate, burglary and motor-vehicle theft. However, the unemployment rate has a significant relationship with 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.

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

	Burglary	Robbery	Larceny	Motor
	MSIH(2)-AR(1)	MSIH(2)-AR(1)	MSI(2)-AR(1)	MSI(2)-AR(1)
Intercepts				
μ_1	-6.049 (-1.571)	-3.289 (-1.270)	-2.773 (-4.098)	-0106 (-1.032)
μ_2	0.677 (0.481)	-1.478 (-0.319)	2.106 (5.729)	0.197 (2.001)
Autoregressive Parameter				
ϕ_1	0.061 (0.511)	-0.015 (-0.194)	0.094 (1.038)	-0.104 (-0.923)
Dummy 1		98.852 (5.370)	-10.989(-4.971)	
Dummy 2		-97.897 (-6.482)		
Standard Errors				
σ_1	22.605	13.359	2.172	0.301
σ_2	9.464	27.824		
Transition Probabilities				
p_{11}	0.902	0.889	0.658	0.959
p_{12}	0.098	0.111	0.342	0.041
p_{21}	0.040	0.147	0.082	0.076
p_{22}	0.960	0.853	0.918	0.924
Durations				
Regime 1	10.18	9.01	2.93	24.33
Regime 2	24.73	6.80	12.17	13.20
Log Likelihood				
Nonlinear	-450.050	-490.750	-268.123	-31.197
Linear	-461.335	-495.241	-273.131	-34.740

t-statistics are in paranthesis.

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

	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. Concordance Index

	Unemployment rate & Burglary	Unemployment rate & Larceny	Unemployment rate & Motor	Uemployment rate & Robbery
CI	0.333	0.261	0.550	0.667
E(CI)	0.414	0.361	0.551	0.555
$\hat{\rho}$	-0.195	-0.292	-0.004	0.255
t-ratio	-1.196	-2.212	-0.027	1.643
CI^{corr}	-0.081	-0.100	-0.002	0.111

Table 4. The Estimated Correlations between Crime Variables and the lagged Unemployment Rate

	Unemployment rate & Burglary	Unemployment rate & Larceny	Unemployment rate & Motor	Unemployment rate & Robbery
1 lag	-0.161	-0.305*	0.003	0.305*
t-ratio	-0.932	-1.851	0.017	1.875
2 lag	-0.171	-0.213	0.011	0.355*
t-ratio	-0.983	-1.552	0.062	2.337
3 lag	-0.137	-0.067	0.018	0.406*
t-ratio	-0.834	-0.666	0.107	2.699
4 lag	-0.103	0.133*	-0.015	0.416*
t-ratio	-0.658	1.853	-0.088	2.676
5 lag	-0.069	0.244*	-0.02	0.384*
t-ratio	-0.455	2.809	-0.108	2.373
6 lag	-0.034	0.247*	0.018	0.352*
t-ratio	-0.231	2.923	0.096	2.206
7 lag	0	0.251*	0.055	0.277*
t-ratio	0	2.989	0.303	1.74
8 lag	0.034	0.254*	0.093	0.245
t-ratio	0.22	2.998	0.511	1.603

An *indicates significant correlations at 10% or lower.

Table 5. Calculate CIs between Crime Variables and Lagged Values of the Unemployment Rate

	Unemployment rate & Burglary	Unemployment rate & Larceny	Unemployment rate & Motor	Unemployment rate & Robbery
1 lag	0.342	0.252	0.550	0.685
2 lag	0.333	0.279	0.550	0.703
3 lag	0.342	0.324	0.550	0.721
4 lag	0.351	0.387	0.532	0.721
5 lag	0.360	0.423	0.523	0.703
6 lag	0.369	0.423	0.532	0.685
7 lag	0.378	0.423	0.541	0.649
8 lag	0.387	0.423	0.55	0.631

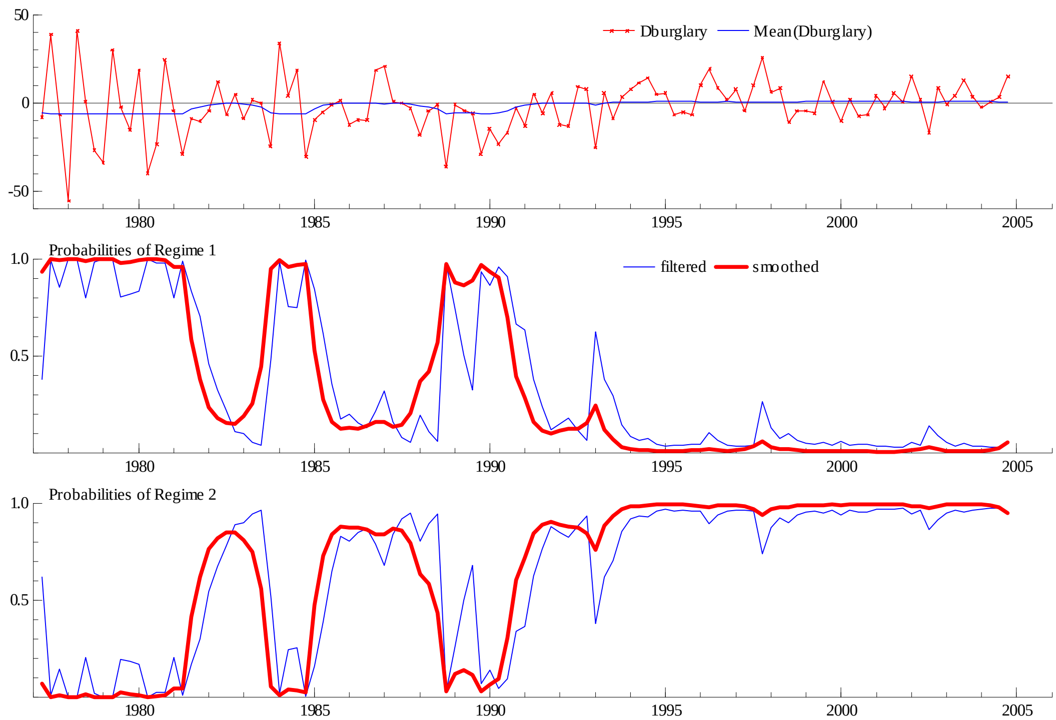

Figure 1. Mean, smoothed, and filtered probabilities for Burglary estimated using a MSIH(2)-AR(1) model

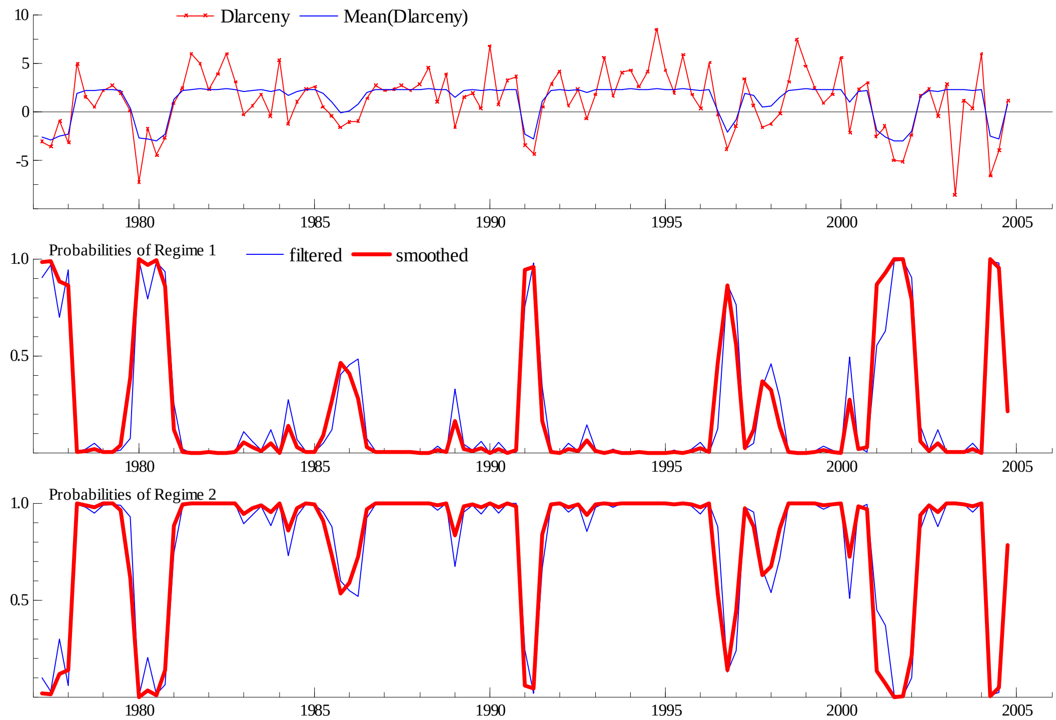

Figure 2. Mean, smoothed, and filtered probabilities for Larceny estimated using a MSI(2)-AR(1) model

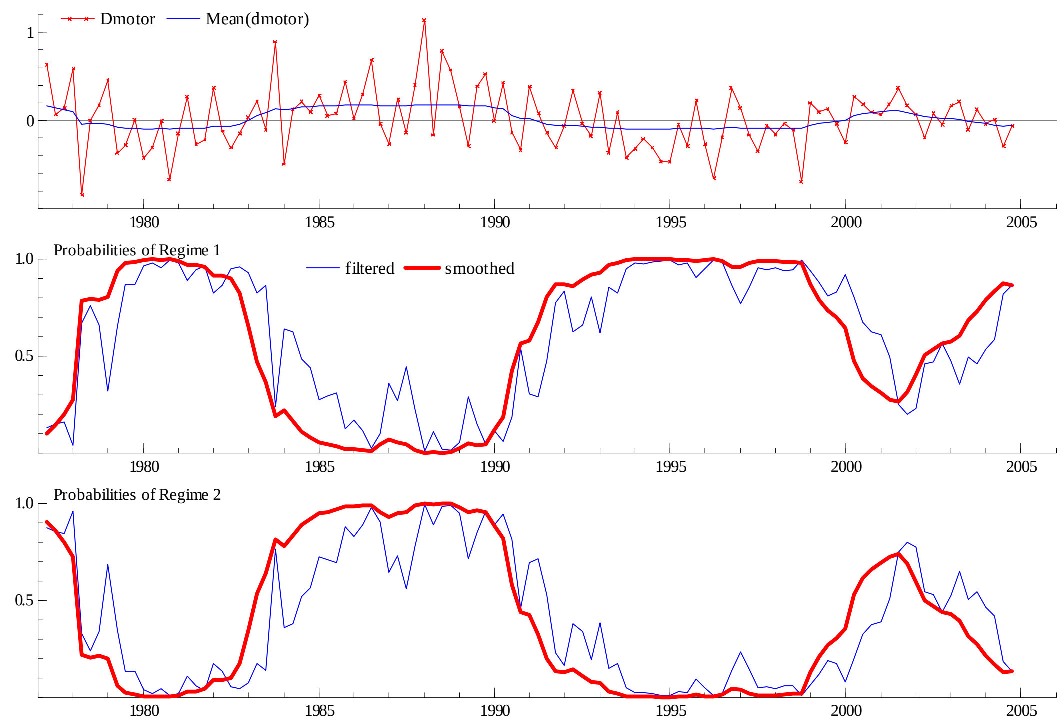

Figure 3. Mean, smoothed, and filtered probabilities for Motor-Vehicle Theft estimated using a MSI(2)-AR(1) model

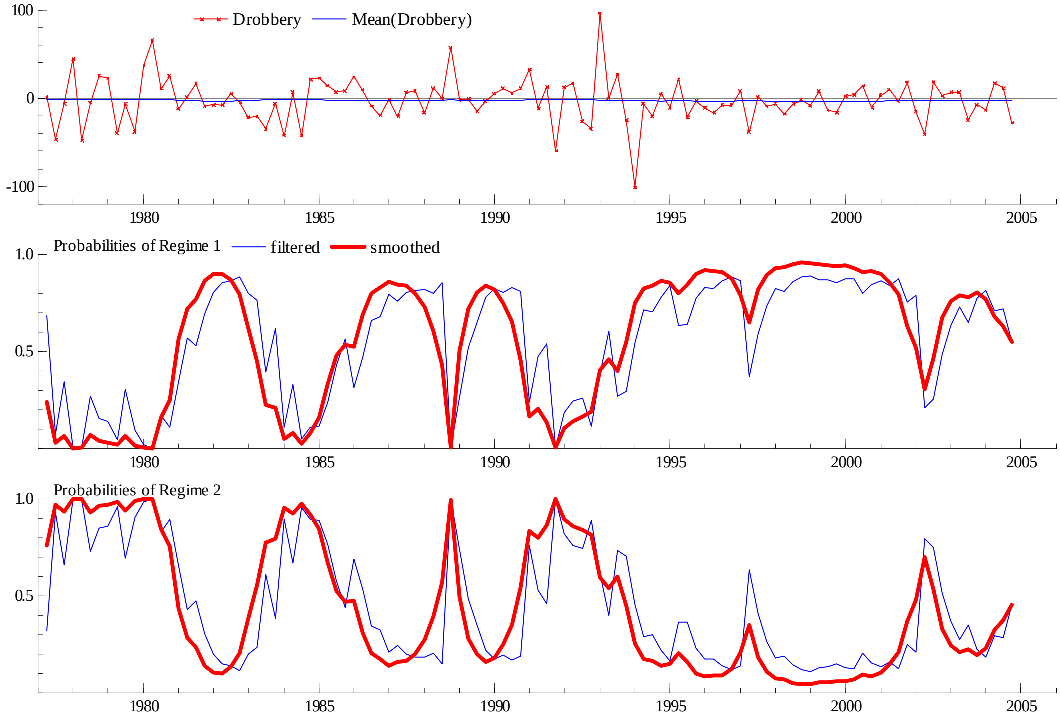

Figure 4. Mean, smoothed, and filtered probabilities for Robbery estimated using a MSIH(2)-AR(1) model

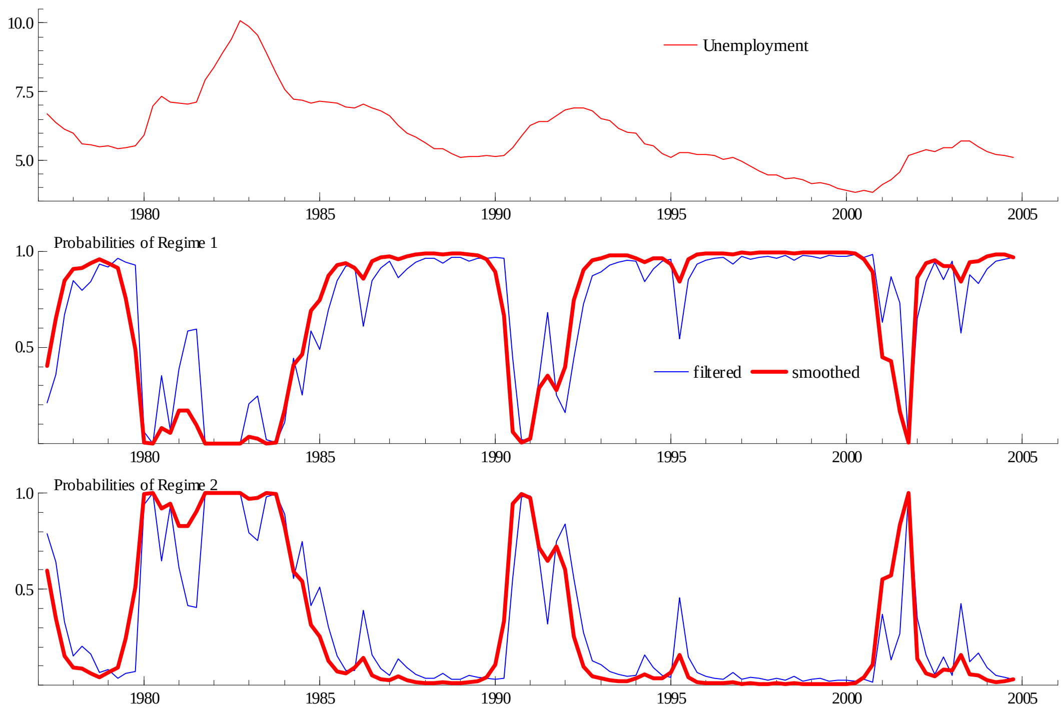

Figure 5. Series, smoothed, and filtered probabilities for the Unemployment Rate estimated using a MSIAH(2)-AR(3)