Business Cycles and Crime. The case of Argentina

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First Draft

Abstract

This study focus on the relationship between crime and business cycle in Argentina, at national and provincial level, using monthly time series for the period 1999-2008. For that end we examine the presence of common factors (interpreted as cyclical components) driving the dynamics of a set of types of crimes and monthly economic activity indicators (EMAE and ISAP). By means of Dynamic Factor Models we identify which type of crime is related to business cycle and if these crimes are leading, lagging or coincident. We find a strong counter-cyclical relationship between total and property crime rates and its typologies and business cycle. Additionally these series are slightly lagged with respect to business cycle. On the other hand, crimes against persons are found to be pro-cyclical and coincident.

Resumen

Este trabajo intenta captar la relación entre crimen y ciclos económicos en Argentina, tanto a nivel nacional como provincial, utilizando series mensuales para el período 1999-2008. Para ello se analiza la presencia de factores comunes (interpretados como componentes cíclicos) que conducen la dinámica de un conjunto de crímenes y de indicadores mensuales de actividad (EMAE e ISAP). Utilizando los Modelos de Factores Dinámicos (DFM) identificamos cuáles crímenes se relacionan con el ciclo económico y si esos crímenes son líderes, coincidentes o rezagadas en relación al ciclo económico. Encontramos una fuerte relación contra-cíclica entre los crímenes totales y contra la propiedad y el ciclo económico. Adicionalmente estas series son levemente rezagadas con respecto al ciclo. Por otro lado, los crímenes contra las personas son pro-cíclicos y coincidentes.

Keywords: Typologies of Crime, Business Cycles, Dynamic Factors Models

JEL Classification Codes: K42, K14, E32

I. Introduction

Since the seminal work by Becker (1968) that provided the first economic theory of crime, many works have been devoted to the study of criminal behavior. According to Becker criminals are rational agents who maximize their utilities dividing their time between legal and illegal activities. This decision comes from a maximization problem in which agents compare expected costs and benefits of legal and illegal activities taking into accounts the probability of being arrested and punished.

Theoretical literature of crime emphasizes on two fundamental aspects: the deterrence effect, related to the probability of being arrested and of being condemned and the social and macroeconomic effect of environment which generates an atmosphere prone to crime, measured by variables such as the unemployment rate, income per capita, income growth, inequality in income distribution, education, among others.

The relationship between economic activity and the crime rate is controversial: An economic expansion could reduce criminal activities but it could also make illegal activities more attractive since it presents better opportunities, although, the potential victims could neutralize this "richness" effect by destining more resources against crime (alarms, bars, etc.).

As discussed in Cantor and Land (1985) there are two different types of effect: motivation effect and opportunity effect. The first one refers to the incentive to commit crime based on bad economic conditions. Hence, during recessions, individuals increase crime participation in order to increase their incomes. The second one works in the opposite way: the opportunities to commit crime increase along with the economic performance. However the impact of opportunity and motivational effect can be different depending on the crime typology under study. For instance, property crimes can be more affected by motivation effects that imply a negative correlation with the economic fluctuations.

This paper tries to shed light on the relationship between economic activity and crime rate for Argentinean Provinces using monthly time series for the period 1999.1-2008.12. We will try to identify common factors between Economic Indicators of Activity (EMAE and ISAP) and a set of types of crime by means of Dynamic Factor Models. Additionally we will try to determine if these types of crime are leading, lagging or coincident with EMAE and ISAP. We are not aware of any study using this method for Argentina, and very few for other countries for example the paper of Detotto and Otranto (2011) for Italy.

The structure of this paper is as follows: After the introduction, Section II presents the theoretical and empirical evidence; Section III shows the Dynamic Factor Model. Section IV presents an overview of data. Section V outlines the empirical model and discusses the econometric results. Section VI concludes.

II. Theoretical and empirical evidence

Theoretical models of crime surge as an extension of Becker seminal paper (1968). According to Becker, criminal behaviour is a decision of rational agents who maximize their utilities by comparing the expected costs and benefits of legal and illegal activities. Agents will engage criminal activities if

$$p_i U_i^{IL}(Y_i - C_i) + (1 - p_i) U_i^{IL}(Y_i) > U_i^{L}(I_i)$$

Where $\boldsymbol{p}$ is the probability of conviction, $\boldsymbol{U^{IL}}$ is the utility derived from illegal activities, $\boldsymbol{Y}$ is the income from illegal activities, while $\boldsymbol{C}$ are the costs associated to illegal activities. It includes direct costs of criminal justice system, as well as the opportunity cost of foregone legal activities. On the other hand $\boldsymbol{U^{L}}$ is the utility of legal activities, and $\boldsymbol{I}$ is the income from legal activities.

In the last decades a vast literature devoted to test the economic model of crime surged, trying to estimate the effect of economic variables (economic growth, unemployment, income inequality) on the crime rate.

The general assumption is that economic fluctuations affect criminal rate by changing the expected income and cost derived from legal to illegal activities. During expansions (recessions) the income of legal activities increases (decreases), but also the opportunities available to criminal activities. The impact of these conflicting effects will depend on the type of crime. Empirical investigations support that the relationship between crime and economic activity mostly depends on the type of crime. For example property crimes are found to be counter-cyclical, while crimes against persons are not as sensitive to economic variations.

One of the first empirical papers linking crime to business cycle was due to Phelps (1929). Phelps correlated an own constructed index of crime to an index of economic conditions. He extracted the secular trend of both indexes and find a negative correlation between them, meaning that crimes increase with poverty and decrease with prosperity. He also compares the movements in different types of crime with an index of economic conditions, finding that property crime is more related to economic conditions.

Later Short (1951) investigates on the relationship between business cycle and crime, specifically robbery and burglary for the US, finding a negative correlation between them, mainly in short cycles. He also finds that in larger cities crime has higher correlations with business cycles than it does in smaller cities.

Cantor and Land (1985), Cook and Zarkin (1985), Corman and Lovitch (1987) and Arvanities and Delfina (2006), using a VAR model find that property crime is counter-cyclical while crimes against persons are not very sensitive to economic fluctuations. The authors detect a motivational and opportunity effect. The motivational effect works in the long-run since "those recently unemployed have a stock of resources that they can use before feeling the effect of unemployment, while the opportunity effect works in the short run because the movements in the employment rate quickly impact the circulation of people and goods, affecting the attitude towards crime". Arvanities and Delfina (2006) examine the influence of business cycle fluctuations on street crime in the conceptual framework of Cantor and Land's paper. In a panel study, they show that an improvement in economic conditions reduce property crimes. Cook and Zarkin (1985) set that economic fluctuations affect crime in different ways depending on the typology of crime. Burglary and theft are found to be counter-cyclical, auto theft pro-cyclical, while cycle has no effect on homicides.

Other studies aim at identifying the short and long run effect of the economic fluctuations on crime rate for different typologies of crime. Pyle and Deadman (1994) for the post war England and Wales period, find a long-run relationship between economic fluctuations (consumption, GDP and unemployment) and crime (burglary, theft and robbery). In addition, Hale (1999) finds a short and long run effect on property crime while unemployment has only a short run effect.

Garret and Ott (2008) in a monthly time series analysis explore the influence of business cycle fluctuations on crime in 20 large cities in the US. They consider seven different types of crimes, concluding that short-run changes in economic conditions, as measured by changes in unemployment and wages, are found to have little effect on city crime across many cities. Property crimes were more likely to be influenced by changes in economic conditions than were more violent crimes. They also find strong evidence that in many cities more arrests follow from an increase in crime rather than arrests leading to a decrease in crime. This is true especially for the more visible crimes of robbery and vehicle theft and suggests that city officials desire to remove these crimes from the public's view.

In line with the present research is the paper of Detotto and Otranto (2011) for Italy. They try to detect the relationships between different typologies of crime and GDP by means of Dynamic Factor Models and whether these crimes are leading, coincident or lagging series. They find that most of the crimes show a counter-cyclical behavior with respect to GDP, i.e., a rise in the economic performance is associated with a decrease in total crime rate. Even more, some property crimes, such as bankruptcy, fraudulent insolvency and embezzlement seem to anticipate the business cycle.

III. The Dynamic Factor Model Approach

The purpose of Factor Model is to extract the common factor from the full set of variables under study. The idea is that each variable can be decomposed into a common part (non-observable factor) and an idiosyncratic noise. The unobserved factors and the disturbances in the equations for the observed variables may follow vector autoregressive structures. Additionally it is possible to classify the series as leading, coincident or lagging with respect to a reference series.[1]

Following Forni et al (2000) and Detotto and Otranto (2011), we consider a vector de ***n*** second-order stationary observed variables, $\boldsymbol{z_t}$ (in this case crime rate and its typologies and GDP), with ***q*** orthogonal common factors contained in the vector $\boldsymbol{y_t}$ of unobservable common factors. Vector $\boldsymbol{z_t}$ is a multivariate time series that can be decomposed as follows:

$$z_t = \chi_t^q + \varsigma_t \tag{1}$$

where ζ_t is the nx1 vector of idiosyncratic components and the common part χ^q is a linear projection de z_t on the space generated by y_t:

$$\chi_t^q = C_q(L)y_t \tag{2}$$

The vector χ^q can be estimated by dynamic principal components as proposed by Forni et al (2000). Given the orthogonality condition between χ^q and ζ_t , the spectral density matrix of z_t, can be decomposed into the spectral density matrices of χ^q and ζ_t respectively

$$\sum(\omega) = \sum\nolimits_{\chi}^{q}(\omega) + \sum\nolimits_{\varsigma}(\omega) \tag{3}$$

Forni et al (2000) show that a consistent estimator of χ^q is obtained as a projection of z_t on the first q eigenvectors of spectral density matrix, associated with the first q eigenvalues in descending order.

We compute the spectral density matrix at different frequencies ω, then we compute the first q eigenvalues and eigenvectors for each Σ(ω) , combining them to obtain the estimation of y_t and $C_q(L)$. In this way the common components χ^q are obtained as a linear combination of lagged, coincident and leading factors y_t. For example, if we identify 2 factors, we can write the common component χ^q as:

$$\chi_t^{2,j} = \sum_{i=-m}^{m} c_{1,i}^{j} y_{1,t-i} + \sum_{i=-m}^{m} c_{2,i}^{j} y_{2,t-i} \tag{4}$$

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[1] Dynamic-factor models have been developed and applied in macroeconomics; see Geweke (1977), Sargent and Sims (1977), Stock and Watson (1989, 1991), and Watson and Engle (1983).

Where χ^q is the cyclical component of the variable *j, c* are weights for the variable *j* Notice that static principal component is a particular case when m=0.

The estimation of the model (1) implies the estimation of q factors. A practical solution is to choose q factors such that they explain a large proportion of the series variance, typically it would be between 50 to 70%.

As we said before, this procedure allows as to classify the series (crime rates) as leading, coincident and lagging with respect to a reference series; in this case, to EMAE and ISAP. We have to extract their cyclical component, contained in the vector χ^q and to compare all the other elements of this vector, each one representing the cyclical components of each crime types with EMAE and ISAP, with it. Then we have to calculate the mean delay which measures the lags in the movements of a series with respect to another one. If the mean delay between the crime series and the EMAE or ISAP is equal to 3, it means that the crimes series leads the economic activity by three periods.

Importantly, DFM captures the common movements of the series contained in z_t without analyzing some cause-effect relationships among variables.

The parameters of dynamic-factor models may be estimated by maximum likelihood. The ML estimator is implemented by writing the model in state-space form and by using the Kalman filter to derive and implement the log likelihood.

IV. Data

The dataset used in this paper consists on monthly observations running from 1999:01 to 2008:12. Crime Data was collected from Registro Nacional de Reincidencia Criminal. Crime rates were defined as the number of reported offences per 10,000 inhabitants. We include total crime rate, property crime rate, distinguishing between robbery, theft and other property crimes, and crimes against persons, including murders at national level. At provincial level we can only classify crimes as crimes against persons and property crimes.

Table 1. Classification of Crime Typology

Crime Group	Typology	Nomenclature
Total Crime		HDEL
Property Crime		DCPRO
	Robbery	ROBT
	Theft	HURT
Crime Against Person		DCPER
	Murder	HOMD
	Intentional Injury	LESD

We approach the national economic activity by the EMAE (Monthly Estimator of National Economic Activity, 1993=100) elaborated by INDEC. This indicator is a good GDP proxy at monthly level.

At provincial level we use as an economic activity indicator a quarterly coincident index ISAP constructed by Muñoz y Asociados. In order to change the periodicity of the index and transform it in a monthly series, we repeat each observation of the quarterly series three times. For example, the first quarterly observation of each year is repeated for January, February and March of that year. We proceed like this, since the quarterly observation is centered in the middle of the corresponding quarter (in this case February). After that we smooth the resulting monthly series by means of X12 ARIMA.

Table 2 shows a summary statistics of national crime rate series and EMAE. Property Crime Rate represents 63.7% of total crimes in the period 2000-2008, and it is by far the largest group. Among property crimes, robberies represent 49.6%, while thefts 40.8%. The second group in importance is crimes against person, with a participation of 19.4%. In this group, intentional injuries have a participation of 55.5%, while murders have a share of 1%. However this group is often studied separately, since it comprises the most sounded cases for its severity.

Table 2. Crime Rate and EMAE Summary Statistics. Argentina

Serie	Period	Obs	HDEL %	Share by Type %*	Mean	Median	SD	Min	Max	SD/Mean
HDEL	1999-2008	120	100.0		276	274	20	241	329	0.07
DCPER	1999-2009	120	19.4	100.0	54	53	7	39	71	0.13
HOMD	2000-2008	112	0.2	1.0	1	1	0	0	1	0.25
LESD	2000-2009	112	10.7	55.1	30	29	4	19	39	0.14
DCPRO	1999-2008	120	63.7	100.0	175	172	21	143	229	0.12
ROBT	1999-2008	120	31.6	49.6	87	84	11	72	116	0.13
HURT	2000-2008	112	25.5	40.8	70	70	10	53	95	0.15
EMAE	1999-2008	120			126	121	22	87	174	0.17

Source: Authors' elaboration *based on data collected from Registro Nacional de Reincidencia Criminal. Minesterio de Justicia de la Nación e INDEC*

Note: %HDEL: Participation in Total Crime (%)
SD: Standar Deviation
* Typologies share do not sum 100, since there are other types of crimes we did not include.

In Table 3 we see the summary statistics at provincial level (see Figure 1A in Appendix). The participation of each province in the total crime looks similar to their participation in national GDP: Buenos Aires, Ciudad Autónoma, Córdoba, Mendoza, Santa Fe and Tucumán represents 70% of total crime just as GDP does. Mean, Median and SD refer to summary statistics of crime rates in the period 1999-2008. It is interested to note the heterogeneous behavior of crime rates in different provinces. For example, Ciudad Autónoma registers the highest rate with a value of 70.1 while Entre Ríos has the lowest one with 22.2 crimes per 10000 inhabitants (see column Max).

Table 3. Total Crime Rate at Provincial Level. Summary Statistics 1999.1-2008.12

Province	Abrev	Share	Mean	Median	SD	Min	Max	SD/Mean
Buenos Aires	BUA	23.9%	16.3	16.6	2.9	12.1	22.8	0.17
Catamarca	CAT	1.2%	31.8	32.0	7.1	23.4	50.4	0.22
Chaco	CHA	2.9%	27.9	27.7	6.3	20.0	44.7	0.23
Chubut	CHU	1.1%	23.4	26.0	4.2	15.4	35.6	0.18
Ciudad Autónoma	CAB	16.6%	57.5	58.8	4.3	48.5	70.1	0.08
Córdoba	CBA	10.6%	32.0	33.8	3.0	27.5	40.5	0.09
Corrientes	COR	2.2%	21.9	22.4	3.5	15.5	32.8	0.16
Entre Ríos	ERS	2.1%	17.0	17.6	1.8	13.9	22.2	0.10
Formosa	FOR	1.0%	19.4	19.6	3.4	14.1	28.6	0.17
Jujuy	JUJ	1.9%	25.6	29.7	9.6	5.5	65.0	0.37
La Pampa	LPP	1.0%	29.0	30.3	5.8	20.5	48.3	0.20
La Rioja	LRJ	0.6%	19.7	19.0	3.8	12.0	28.3	0.19
Mendoza	MEN	7.8%	41.8	47.4	3.3	42.5	58.3	0.08
Misiones	MIS	1.8%	16.3	17.5	3.0	11.3	25.9	0.19
Neuquén	NEU	2.5%	46.4	49.9	5.0	37.8	63.7	0.11
Río Negro	RNG	1.6%	25.5	26.5	4.4	16.3	39.7	0.17
Salta	SAL	3.7%	27.9	28.4	9.1	17.8	53.2	0.33
San Juan	SJU	2.2%	33.0	32.8	6.5	19.2	57.8	0.20
San Luis	SLU	0.8%	18.6	19.1	3.6	12.0	29.6	0.19
Santa Cruz	SCZ	0.8%	39.1	40.0	6.7	23.0	54.0	0.17
Santa Fe	SFE	8.8%	26.7	28.6	4.1	19.6	36.4	0.15
Santiago del Estero	SGO	1.6%	19.0	18.8	3.0	14.2	29.5	0.16
Tierra del Fuego	TDF	0.3%	27.1	29.5	4.2	18.6	38.2	0.16
Tucumán	TUC	2.8%	20.3	20.3	3.1	13.3	27.1	0.15
Argentina	**ARG**	**100%**	**27.2**	**27.2**	**1.8**	**22.3**	**32.4**	**0.07**

***Source**:* Authors' elaboration *based on data collected from Registro Nacional de Reincidencia Criminal. Minesterio de Justicia de la Nación.*

Note: Share %: Participation in Total Crime (%)
SD: Standard Deviation

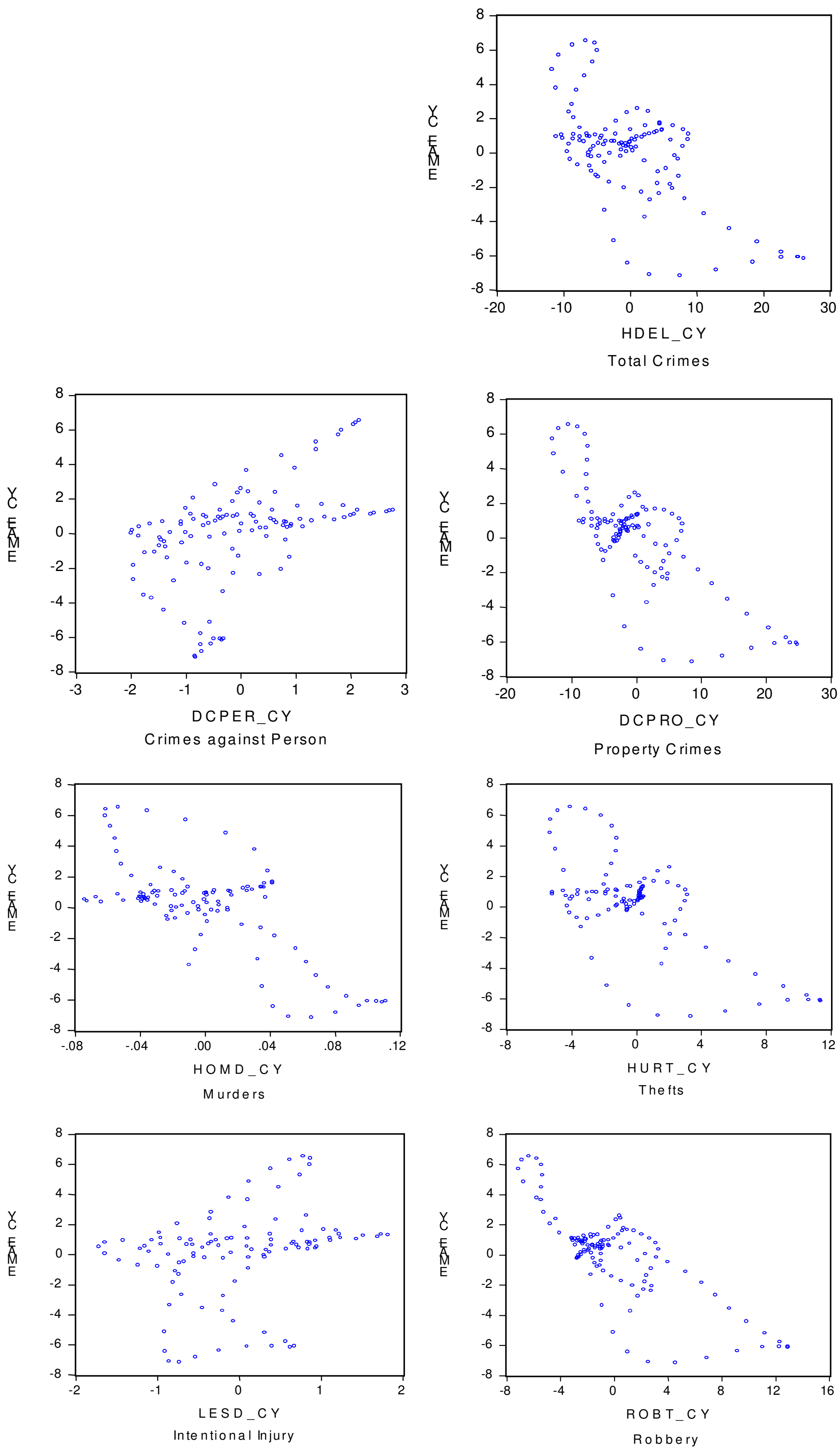
Table 4 Correlations between Crime Rates and EMAE- Trend-Cycle components Argentina

	HDEL	DCPER	HOMD	LESD	DCPRO	HURT	ROBT	EMAE
HDEL	1.00	-0.12	0.63	0.37	0.89	0.84	0.92	**-0.54**
DCPER		1.00	-0.73	0.69	-0.56	-0.62	-0.44	**0.84**
HOMD			1.00	-0.41	0.87	0.83	0.84	-0.81
LESD				1.00	-0.01	0.01	0.01	0.23
DCPRO					1.00	0.98	0.97	**-0.83**
HURT						1.00	0.91	-0.90
ROBT							1.00	-0.70
EMAE								**1.00**

In Table 4 we present the simple correlations between crime rate and its typologies and EMAE. We first see a high positive relationship between crimes against persons (DCPER) and EMAE of 0.84. This correlation is also positive but low (0.23) for intentional injury (LESD) while murders present a high negative correlation (-0.81). The correlation for property crimes is negative and high (-0.83) and also for theft (-0.9) and robberies (-0.7)

Figure 1 shows a scatter plot of the national economic activity growth cycle and crime rates growth cycle for total crime, and its typologies. In order to obtain the cyclical component of the series, we used Hodrick and Prescott filter at the predetermined level of the parameter. We can clearly see a negative relationship between the cyclical component of total crime, property crime and its typologies and of the EMAE. For crimes against persons and its typologies, there is not such clear relationship, in the case of murders, the relationship looks negative. These results are consistent to the ones presented in Table 4. (At provincial level see Figure 2A in Appendix)

Figure 1. Scatter Plot – Crime Rates and EMAE



Empirical Results

We seasonally adjusted all the series by means of the X12 ARIMA routine. Next, we transformed these series into logarithms and detrended them using the Hodrick and Prescott filter. Then, we tested for stationary to the resulting series, since the DF modes requires stationary series. Using the Phillips and Perron (1988) test, we could not reject stationarity at a significance level of 5%.

After that, we extracted the common part of the series, and classified them according to their temporal relationship with the reference series, in this way we could determine if crime rates are coincident, leading or lagging respect to the EMAE at national level and to the ISAP at provincial level.

V.I National Level

Bivariate Model: Total Crime and EMAE

We first specify a DFM with n=2 (n represents the number of series), and we set the minimum explained variance at 50%. In this way, the number of factors chosen is 1.

Table 5: Correlation between common parts of total crime and EMAE.

	(*)Lags										
	-5	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**
EMAE	0.045	0.097	0.442	0.586	0.765	**1.000**	0.765	0.586	0.442	0.097	0.045
HDEL	-0.09	-0.34	-0.43	-0.68	**-0.75**	-0.46	-0.44	-0.36	-0.09	-0.01	0.086

According to Table 5 the correlation between total crime and EMAE is negative; indicating that total crime is counter-cyclical. Additionally, as the maximum correlation is in lag (-1), crime is lagged related to the reference cycle. This behavior seems to be in line with the theory of the motivation effect (Cantor and Land 1985), meaning that during recessions, individuals increase crime participation in order to increase their incomes.

In addition, Table 6 shows that the variance explained by the common component is 74.5%, meaning that total crime rate has a significant common component with EMAE.

Table 6: Ratio common component variance over series variance

Series	**Ratio Value**
EMAE	0.626
HDEL	0.745

Model 3-variate: Crime against persons, Property Crime and GDP

Next we repeat the analysis performed in the previous section but with the two groups of crime considered: crimes against persons and property crimes rates.

We specify a DFM with n=3, and by setting the minimum explained variance at 50% we choose the number of factors, equal to 1

Table 7: Correlation between common parts of Crimes against persons, Property crimes and EMAE.

Series	**(*)Lags**										
	-5	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**
EMAE	-0.12	0.04	0.30	0.61	0.88	**1.00**	0.88	0.61	0.30	0.04	-0.12
DCPER	0.04	0.04	-0.03	-0.06	0.09	**0.22**	0.15	-0.03	0.03	0.00	0.00
DCPRO	0.15	-0.07	-0.43	-0.72	**-0.82**	-0.77	-0.70	-0.51	-0.23	0.03	0.17

Table 7 shows that the correlation between crime against persons and EMAE is positive, indicating that is pro-cyclical. Additionally, crime against persons is a coincident series since the maximum correlation is in lag (0), this behavior is consistent with the mean delay classification. On the other hand property crime is counter-cyclical and slightly lagged, which is again consistent with the mean delay classification. The negative correlation in property crime may be well explaining the negative correlation observed in total crime, given the high participation that property crime has on total crime (see Table 2). Table 8 shows that the variance explained by the common component is 60% for crimes against persons and 44% for property crime.

Table 8: Ratio common component variance over series variance

Series	**Ratio Value**
EMAE	0.551
DCPER	0.603
DCPRO	0.442

Model 5-variate: Murders, Intentional Injuries, Robbery, Thefts and EMAE

We focus on the analysis of four crime variables along with the EMAE. We specify a DFM with n=5, and select factors so that they explain at least 50% of the total variance. We then choose the number of factors that is again equal to 1.

Table 9 illustrates that theft and robberies behave counter-cyclically and slightly lagged with reference to business cycle, just as property crimes do. This behavior is in coincidence with the mean delay classification (Column 6 of Table 10).

Among crimes against persons, murders are counter-cyclical and coincident, while intentional injuries are pro-cyclical and slightly lagged. The behavior of these series is not consistent with the mean delay classification, by which murders are slightly leading and intentional injured is coincident (Column 6 of Table 10)

Table 9: Correlation between common parts of Murders, Intentional Injuries, Robbery, Thefts and EMAE. Argentina

Series	**(*)Lags**										
	-5	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**
EMAE	-0.02	0.03	0.17	0.45	0.79	**1.00**	0.79	0.45	0.17	0.03	-0.02
HOMD	-0.02	-0.03	-0.05	-0.06	-0.03	**-0.35**	-0.26	-0.11	-0.01	0.01	0.01
LESD	-0.03	-0.03	-0.02	0.07	**0.28**	0.22	0.23	0.05	0.02	0.05	-0.01
ROBT	0.02	0.05	-0.16	-0.42	**-0.53**	-0.53	-0.48	-0.26	-0.09	-0.03	-0.03
HURT	0.01	0.02	-0.16	-0.40	**-0.47**	-0.34	-0.28	-0.12	-0.04	-0.01	-0.02

In column 4 of Table 10 shows that the variance explained by the common component for the four typologies of crimes have significant common component with EMAE, since their values are higher than 50%.

Table 10: Analysis of the Common Parts of Crime typologies and EMAE

Series	**Common parts**	**Lags(1)**	**RCCV(2)**	**Phase classification(3)**	**Classification (4)**
EMAE			0.717		
HOMD	-0.349	0	0.597	-	Leading
LESD	0.281	-1	0.737	+	Coincident
ROBT	-0.531	-1	0.765	-	Lagging
HURT	-0.471	-1	0.826	-	Lagging

(1) Number of lag with highest cross-correlation between common parts of series

(2) Ratio Common Component Variance over series variance

(3) (+) and (-) indicates the crime common component is in phase and in opposite phase respectively with respect to the common component of the EMAE

(4) Mean Delay Classification

V.II Provincial Level

At provincial level we only have crimes classified into crimes against person and property crimes, so we can only build a bivariate and 3-variate model. As we explained in section IV, we use an economic coincident indicator index ISAP. We present the results in Table 11 and Table 12

Bivariate Model: Total Crime and ISAP

We first specify a DFM with n=2, and we set the minimum explained variance at 50%. In this way, the number of factors chosen is 1.

Table 11: Analysis of the Common Parts of Total Crime and ISAP. Bivariate Model

Province	Abrev[(1)]	RCCV[(2)]		Phase classification[(3)]	Classification[(4)]
		ACT-INDEX	**DEL-TOT**		
Buenos Aires	BUA	0.743	0.550	-	Lagging
Catamarca	CAT	0.789	0.740	-	Lagging
Chaco	CHA	0.774	0.716	-	Lagging
Chubut	CHU	0.814	0.623	+	Leading
Ciudad Autónoma	CAB	0.785	0.694	-	Lagging
Córdoba	CBA	0.796	0.577	-	Lagging
Corrientes	COR	0.796	0.747	-	Lagging
Entre Ríos	ERS	0.804	0.590	+	Coincident
Formosa	FOR	0.800	0.597	-	Leading
Jujuy	JUJ	0.777	0.602	+	Coincident
La Pampa	LPP	0.770	0.719	-	Lagging
La Rioja	LRJ	0.713	0.662	+	Coincident
Mendoza	MEN	0.809	0.638	-	Lagging
Misiones	MIS	0.791	0.617	-	Leading
Neuquén	NEU	0.776	0.777	-	Lagging
Río Negro	RNG	0.799	0.611	+	Lagging
Salta	SAL	0.775	0.514	-	Leading
San Juan	SJU	0.816	0.676	-	Lagging
San Luis	SLU	0.783	0.698	+	Coincident
Santa Cruz	SCZ	0.796	0.659	-	Leading
Santa Fe	SFE	0.791	0.616	-	Lagging
Santiago del Estero	SGO	0.807	0.621	+	Lagging
Tierra del Fuego	TDF	0.793	0.674	-	Lagging
Tucumán	TUC	0.794	0.718	-	Lagging
Argentina (ISAP)	**ARG**	**0.787**	**0.746**	**-**	**Lagging**
Argentina (EMAE)	**ARG**	**0.626**	**0.745**	**-**	**Lagging**

(1) Provinces identification
(2) Ratio Common Component Variance over series variance

(3) (+) and (-) indicate the crime common component is in phase and in opposite phase respectively with respect to the common component of the ISAP (provinces) or EMAE (National).

(4) Mean Delay Classification

According to Table 11, most provinces are counter cyclical (17 out of 24) that include the most representative provinces measured by their GDP (City and Province of Buenos Aires, Santa Fe, Córdoba, Mendoza and Tucumán). These results are consistent with the ones found at national level (see Table 5). The others 7 provinces are pro cyclical.

We also find that total crime in 15 out of 24 provinces are lagged related to the reference cycle, similar to the results obtained at national level. On the other hand, total crime in the rest of the provinces is coincident (4) and leading (5).

In most of the provinces the motivation effect hold, meaning that during recessions, individuals increase their crime participation.

Model 3-variate: Crime against persons, Property Crime and ISAP

Next we repeat the analysis performed in the previous section but with the two groups of crime considered: crimes against persons and property crimes rates.

We specify a DFM with n=3, and by setting the minimum explained variance at 50% we choose the number of factors, equal to 1.

Table 12 shows that in most of the provinces (20 out of 24), property crime is counter cyclical and in the rest of the provinces pro cyclical (Chubut, Jujuy, La Rioja and San Luis). This needs further investigation, since it might be due to the data or to the behavior of property crime in these provinces.

Additionally, property crime in 13 provinces is lagged related to the reference cycle just as it happened at national level, in two provinces is coincident and in the rest of them is leading (9).

On the other hand, crimes against persons in 16 out of 24 provinces is pro cyclical, while in the other 8 is counter cyclical. For this type of crime, 11 provinces are lagged, 7 coincident and 6 are leading related to the reference cycle. At national level crimes against persons is a coincident series.

Table 12: Analysis of the Common Parts of Crime and business cycle by province. 3-variate Model

Province	Abrev[(1)]	RCCV[(2)]			Phase Classif.[(3)]		Classification[(4)]	
		ACT-INDEX	DCPRO	DCPER	DCPRO	DCPER	DCPRO	DCPER
Buenos Aires	BUA	0.626	0.439	0.444	-	-	Lagging	Leading
Catamarca	CAT	0.741	0.497	0.356	-	-	Leading	Lagging
Chaco	CHA	0.749	0.418	0.389	-	+	Lagging	Leading
Chubut	CHU	0.781	0.486	0.383	+	+	Leading	Leading
Ciudad Autónoma	CAB	0.742	0.590	0.528	-	-	Lagging	Lagging
Córdoba	CBA	0.736	0.462	0.399	-	+	Lagging	Lagging
Corrientes	COR	0.747	0.572	0.328	-	+	Lagging	Lagging
Entre Ríos	ERS	0.751	0.135	0.653	-	+	Leading	Coincident
Formosa	FOR	0.770	0.401	0.396	-	+	Leading	Coincident
Jujuy	JUJ	0.397	0.786	0.794	+	+	Coincident	Coincident
La Pampa	LPP	0.696	0.575	0.456	-	-	Lagging	Lagging
La Rioja	LRJ	0.764	0.217	0.585	+	-	Lagging	Leading
Mendoza	MEN	0.736	0.520	0.286	-	+	Lagging	Coincident
Misiones	MIS	0.738	0.425	0.397	-	+	Leading	Coincident
Neuquén	NEU	0.780	0.846	0.300	-	+	Lagging	Lagging
Río Negro	RNG	0.773	0.392	0.549	-	+	Leading	Lagging
Salta	SAL	0.664	0.430	0.443	-	+	Leading	Lagging
San Juan	SJU	0.777	0.565	0.360	-	+	Lagging	Coincident
San Luis	SLU	0.755	0.478	0.299	+	+	Coincident	Coincident
Santa Cruz	SCZ	0.794	0.545	0.317	-	+	Leading	Leading
Santa Fe	SFE	0.773	0.357	0.400	-	-	Lagging	Leading
Sant. del Estero	SGO	0.792	0.444	0.565	-	+	Leading	Lagging
Tierra del Fuego	TDF	0.753	0.448	0.526	-	-	Lagging	Lagging
Tucumán	TUC	0.735	0.451	0.586	-	-	Lagging	Lagging
Argentina (ISAP)	**ARG**	**0.727**	**0.611**	**0.370**	**-**	**+**	Lagging	Coincident
Argentina (EMAE)	ARG	0.551	0.442	0.603	-	+	Lagging	Coincident

(1) Provinces identification (2) Ratio Common Component Variance over series variance (3) (+) and (-) indicates the crime common component is in phase and in opposite phase respectively with respect to the common component of the ISAP (provinces) or EMAE (National) (4) Mean Delay Classification

V. Conclusions

This paper studied the relationship between crime and its typologies and business cycle in Argentina at national and provincial level using monthly time series for the period 1999-2008. The purpose of this paper was to determine common factors among crime rate and its typologies and the economic activity. We do no aim at determining a causal effect relationship.

For that end we examined the presence of common factors (interpreted as cyclical components) driving the dynamics of a set of types of crimes and EMAE at national level and ISAP at provincial level. By means of Dynamic Factor Models (DFM) we identified which type of crime is related to business cycle and if these crimes are leading, lagging or coincident using mean factor classification.

At national level, we found that crimes against persons are pro-cyclical and coincident, while property crimes are counter-cyclical and slightly lagged.

We additionally analyzed four typologies of crime. Theft and Robberies, which belong to property crime group, are counter-cyclical and slightly lagging. In property crimes the classification of series by mean delay or by the highest lag correlation gives the same result.

Murders and Intentional Injury belongs to crimes against person's category, we find that murders are counter-cyclical and coincident or leading, depending on the method we use: highest lag correlation or mean delay classification respectively. Intentional injury is pro-cyclical and lagging or coincident depending again on which method of classification we use.

At provincial level we only have total, property crimes and crime against persons. In general, most of the provinces performed equally to the national level for that type of crimes. However the behavior of all the provinces is not homogeneous. Those provinces that behave differently than the average are mostly those that have a small participation in the Argentinean GDP.

These results are in line with those obtained by Detotto and Otranto (2011) who also find that most of the crimes are counter cyclical and lagging.

As we pointed out at the beginning, the relationship between economic activity and the crime rate is controversial: An economic expansion could reduce criminal activities but it could also make illegal activities more attractive since it presents better opportunities. As discussed in Cantor and Land (1985) there are two different types of effect: motivation effect and opportunity effect. The first one describes a counter-cyclical behavior while the second one works in the opposite phase. We find, as Cantor and Land did, that property crimes can be more affected by motivation effect which implies a negative correlation with the economic fluctuations. Even more, property crimes are counter-cyclical, while crimes against persons are not as sensitive to economic variations.

As a future agenda we will intent to update our dataset. However we are aware that it will not be an easy task, due to the central administration policy related to statistics.

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VIII Appendix

Figure 1A: Boxplots: summary statistics at provincial level. Total crime rates

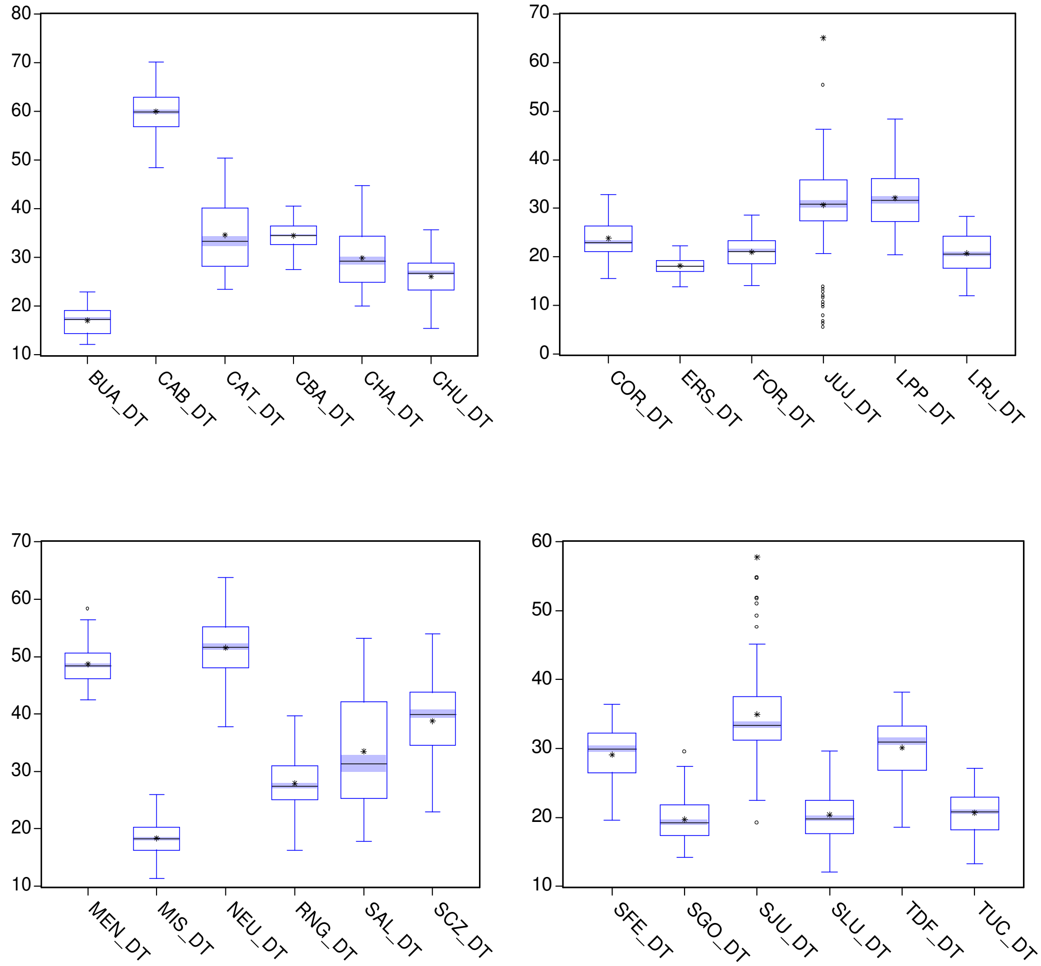
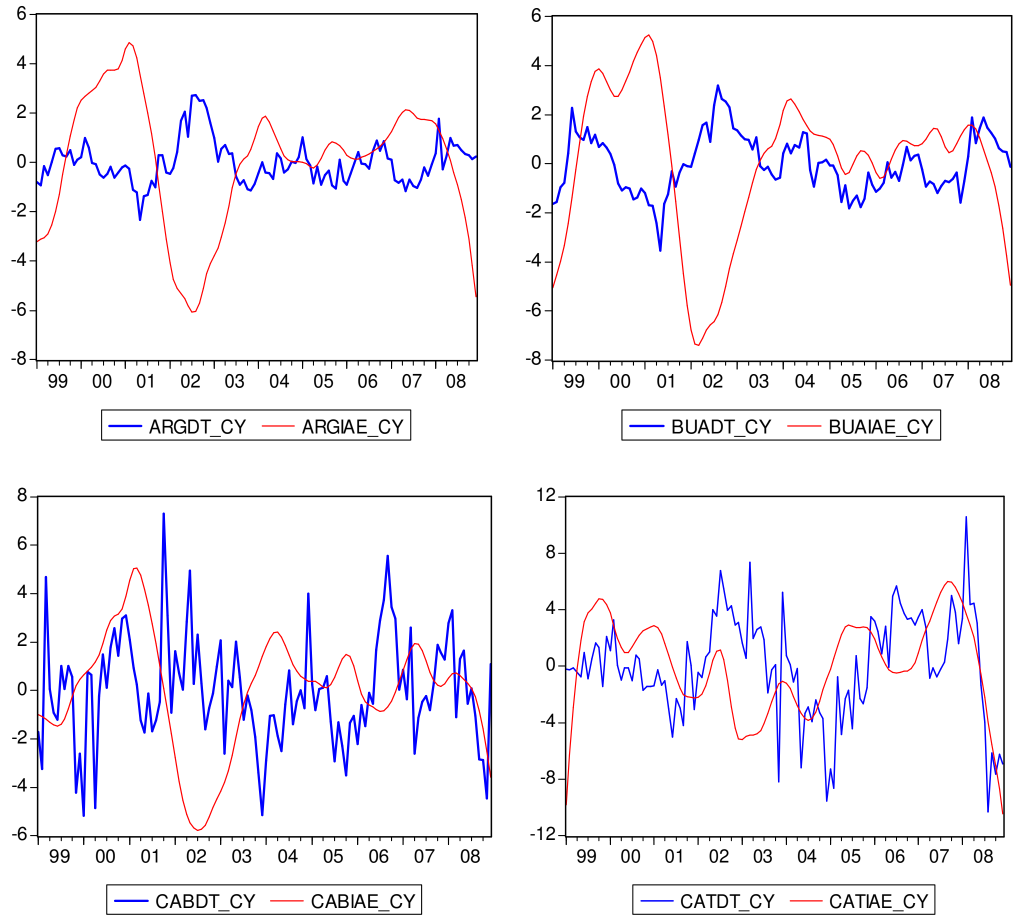
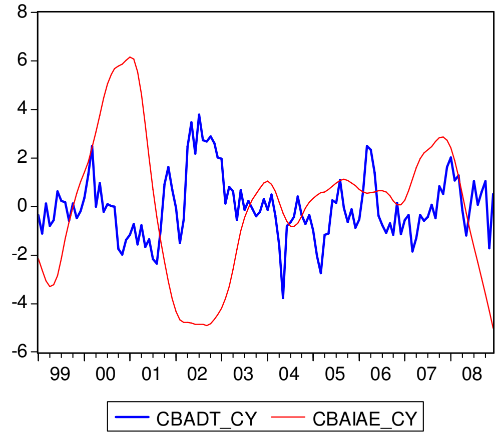


Figure 2A Total Crime by province and ISAP. Cycles (CY)

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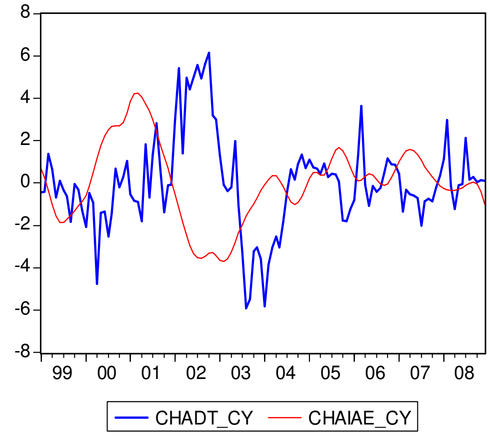
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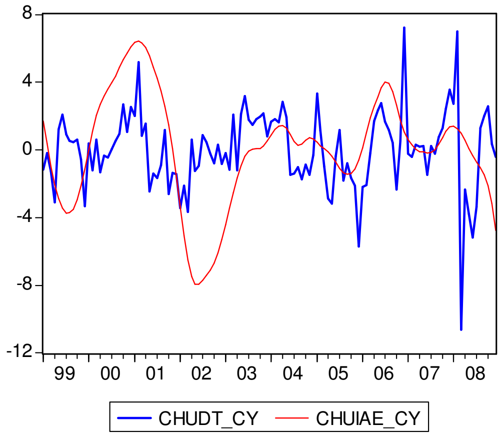
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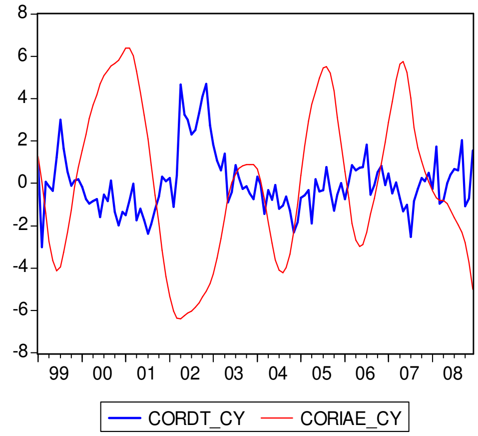
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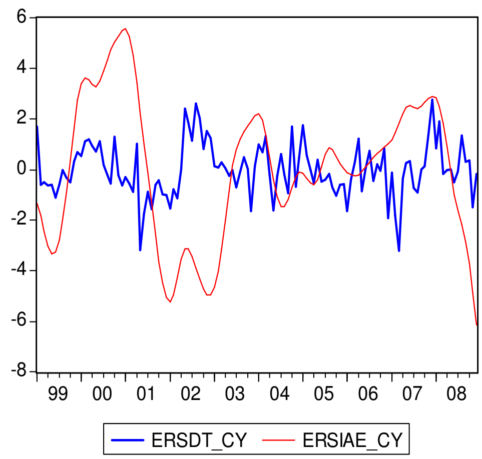
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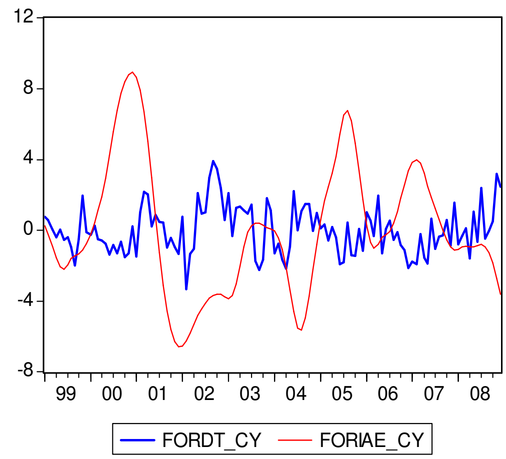
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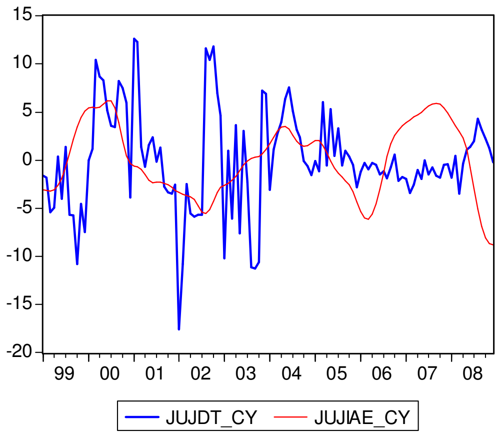
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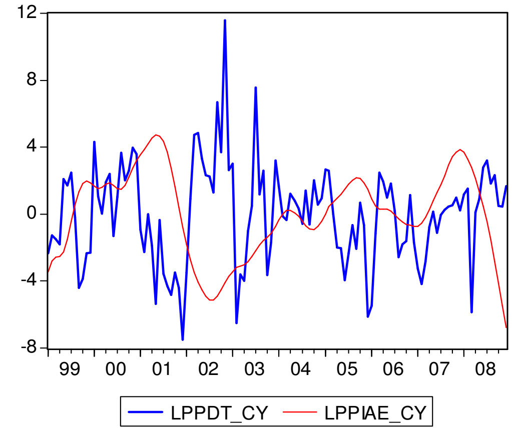
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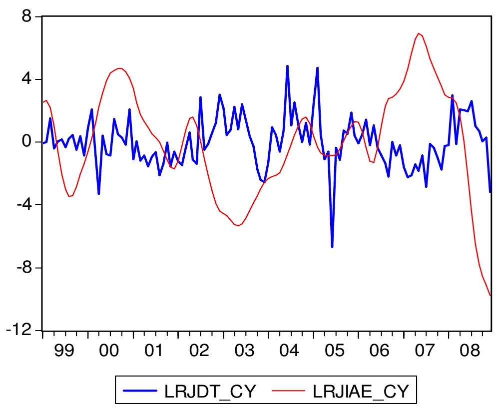
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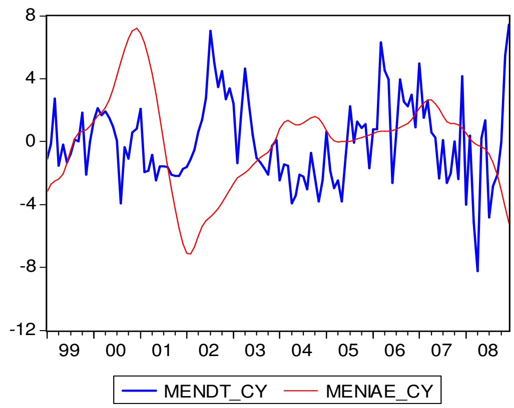
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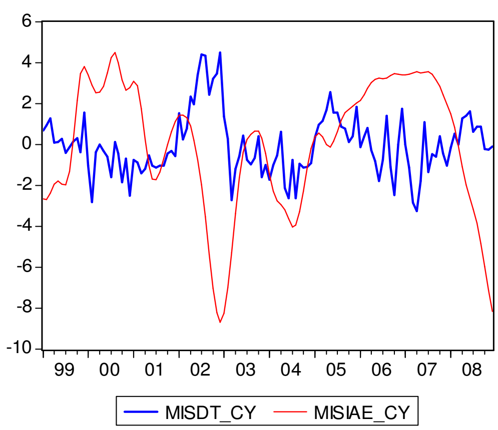
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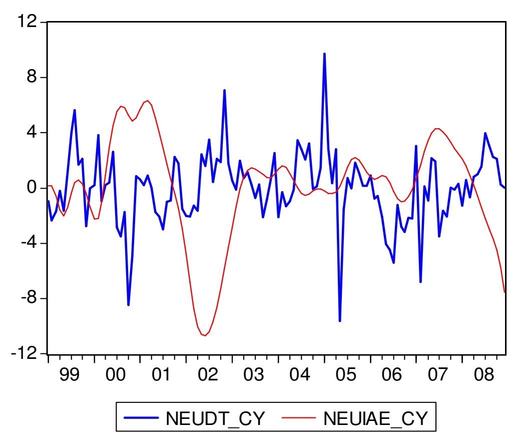
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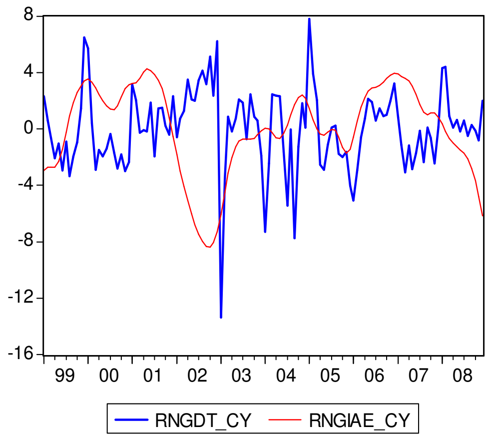
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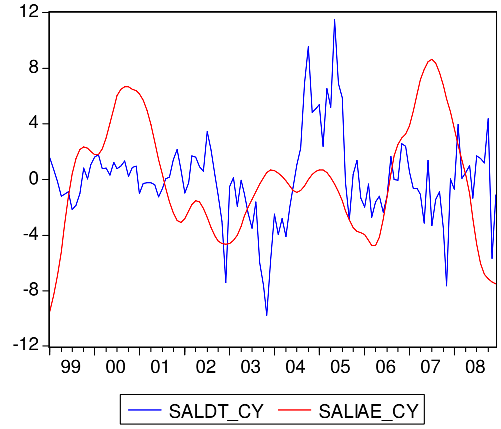
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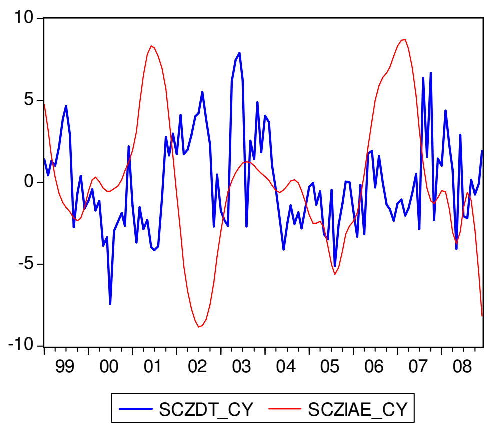
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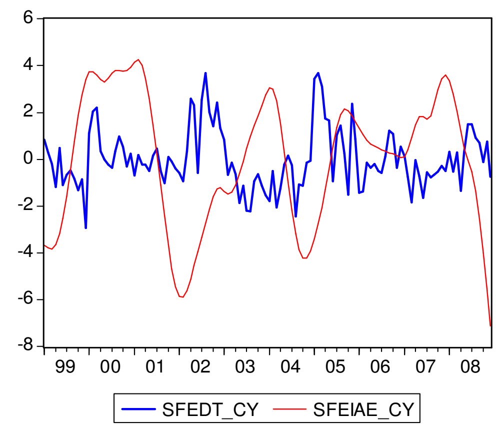
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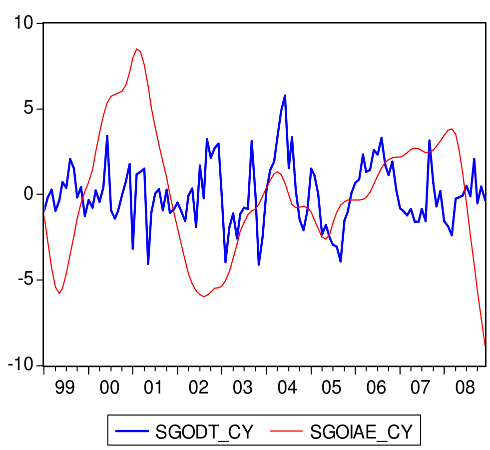
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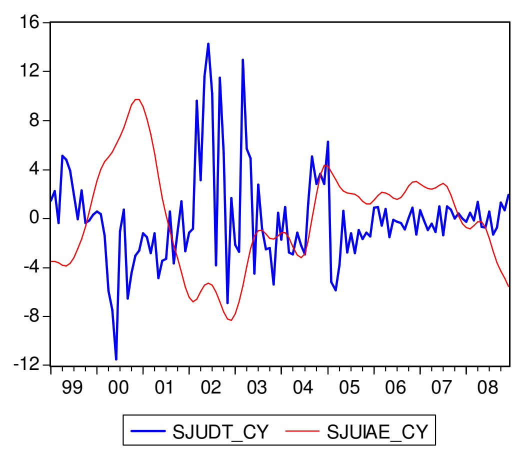
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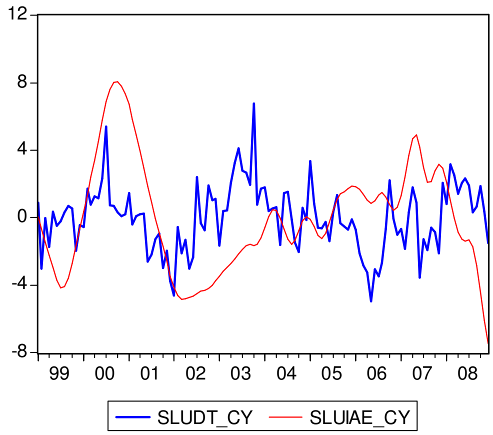
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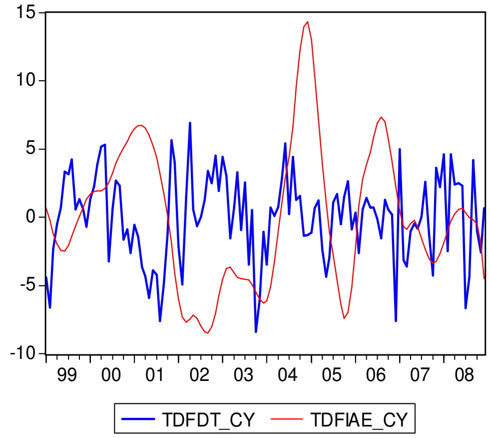
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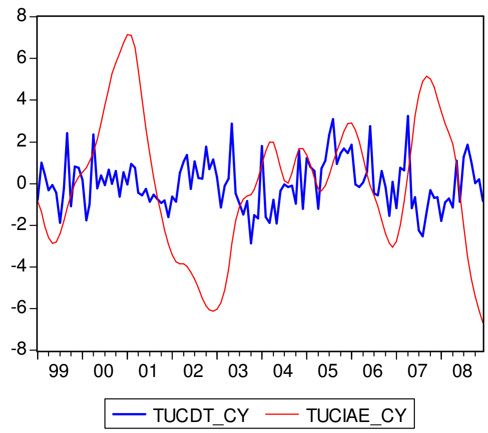
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