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CYCLES IN CRIME AND ECONOMY: LEADING, LAGGING AND COINCIDENT BEHAVIORS

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Cycles in Crime and Economy:
Leading, Lagging and Coincident Behaviors

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Abstract

In the last decades, the interest in the relationship between crime and business cycle has widely increased. It is a diffused opinion that a causal relationship goes from economic variables to criminal activities. This work aims to verify this proposition by using the dynamic factor model to analyze the common cyclical components of Gross Domestic Product (GDP) and a large set of criminal types. Italy is the case study for the time span 1991:1 - 2004:12. The purpose is twofold: on the one hand we verify if such a relationship does exist; on the other hand we select what crime types are related to the business cycle and if they are leading, coincident or lagging.

The study finds that most of the crime types show a counter-cyclical behavior with respect to the overall economic performance, but only a few of them have an evident relationship with the business cycle. Furthermore, some crime offenses, such as bankruptcy, embezzlement and fraudulent insolvency, seem to anticipate business cycle, in line with recent global events.

Keywords: business cycle, crime, common factors, dynamic factor models.
Jel classification: C38, E32, K0

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1 Introduction

Since the seminal paper of Becker (1968), crime is considered a labor phenomenon, as opposed to a legal activity. In this view, the criminal is a rational agent who, by maximizing his utility given his budget constraint, chooses between legal and illegal activities. Hence, he engages in an illicit activity only if his expected net value is higher than the expected gain from a legal activity. In the last decades, a vast literature has theorized the rational behavior of criminal agents, highlighting the relationship between crime efforts and macroeconomic variables. In line with the theoretical approach, a number of scholars have tried to test the economic crime model (see Buonanno, 2003, for a survey of the literature on crime determinants). They estimate the effect of economic variables, such as economic growth, income, income inequality, unemployment rate, on crime rates. The general assumption is that economic fluctuations affect criminal behavior by varying the incentive and the propensity to commit crime. Hence, crime series are expected to be driven by business cycle and quite similar pattern fluctuations have indeed been observed between crime rates and the business cycle. Surprisingly, even if the determinants of crime have been widely investigated, the relationship between crime and the economic cycle is far from being clearly defined.

A number of works measure the effect of the business cycle on crime rate implementing univariate time series or VAR approaches (Cantor and Land, 1985, Cook and Zarkin, 1985, Corman et al., 1987, Arvanites and Defina, 2006). In general, the findings show that property crimes seem to have a significant counter-cyclical component while crimes against persons are not as sensitive to variations in economic activity. In a recent study, Rosenfeld (2009) shows that violent crime can be stimulated by economic conditions (the unemployment rate, real GDP per capita, and the Index of Consumer Sentiment) indirectly through a rise in property crimes (robbery, burglary and motor vehicle theft).

By using annual data, Cook and Zarkin (1985) analyze the impact of economic fluctuations on robbery, burglary, auto theft and homicide in the US in the time span 1933-1981. By applying parametric and nonparametric approaches, they find that crimes such as robbery and burglary are counter-cyclical with respect to economic growth, while auto theft is pro-cyclical. Moreover, economic performance seems to have no effect on the homicide rate. The authors point out that long term economic trends have a higher impact than short ones. Similar results are found by Gould et al. (2002), who find that the long-term wage trends explain more than 50% of the increase in both property and violent crimes in the US (annual county-level data from 1979 to 1997). By using annual panel data, Arvanites and Defina (2006) show that an improving economy reduces property crimes.

Cantor and Land (1985) theorize the macroeconomic relationship between economic performance and criminal activity. They indicate two opposite strands of criminal behavior: motivation effect and opportunity effect. The former refers to the incentive to commit crime coming from bad economic conditions. Hence, during recessions, individuals increase crime participation in order to increase their disposable income. The latter works in the opposite way: the opportunities to commit crime (widespread availability of goods and profitable illegal activities) increase along with the economic performance. According to Cantor and Land (1985), the motivational effect works in the long-run because "those recently made jobless have a stock of resources (savings, unemployment, welfare) that they can immediately draw upon and first must exhaust before feeling the financial pinch of unemployment" (Paternoster and Bushway, 2001), while the opportunity effect works in the short run because the ups and downs of the employment rate quickly impact the circulation of people and goods, affecting the attitude towards crime. Unfortunately, as argued by Paternoster and Bushway (2001), the relationship between crime and the business cycle may not be so straightforward: the counter and pro-cyclical behavior to commit crime can be fuelled by different criminal characteristics or attitudes, and not just by temporal lag effects.

One of the key lessons from this branch of literature is the existence of a linkage between illegal activities and the business cycle, but the empirical evidence of such relationship is affected by cross-sectional or longitudinal aggregate data problems. The use of aggregate data could not highlight the presence of differences among macro-groups of crime because they are the sum of several typologies with different cyclical behavior. Moreover, high frequency data allow to identify trend-cycle components of the series under study and facilitate the comparison with respect to the business cycle.

In this study, we propose to analyze the cyclical component of a large number of crime types and the relationship between such illegal activities and the business fluctuations. We employ a multivariate approach to classify the crime types in terms of their behavior with respect to the business cycle (pro and counter cyclical, leading, coincident or lagging) and their relationship with the business cycle. A possible solution is the use of a Dynamic Factor Model (DFM), successful both in the parametric and non parametric form (Sargent and Sims, 1977, Stock and Watson, 1993). The large number of crime types can imply difficulties for the implementation of the parametric approach. A feasible model is the non parametric DFM proposed by Forni et al. (2000)[1].

This approach has been successfully used in several economic analysis; see, for example, Altissimo et al. (2001) and Forni et al. (2001) for the analysis of the Euro Area business cycle; Favero et al. (2004) for the analysis of monetary policy; Mansour (2003) for the study of common sources of fluctuations to estimate a world business cycle with a large set of countries . Briefly, the basic idea of DFMs is that a common nonobservable factor drives the dynamics of all variables. The purpose of these models is to capture this common element, cleaning each variable from its idiosyncratic components. I would then be possible to classify automatically the variables for the behavior of the common component with respect to a reference variable, which in our case is constituted by the business cycle. The automatic classification is a by-product of the decomposition procedure of the nonparametric DFM.

In this work, we apply the nonparametric DFM to 22 crime types in Italy in the period 1991 to 2004 (monthly data). The study achieves several goals. First, by using monthly data, it leads to a robust quantitative analysis of crime series. Secondly, it allows understanding whether and what types of crime show a cycle; so far this aspect has been quite neglected in the literature. Furthermore, we perform a comparison between crime and economic fluctuations to check for similarities, overlap periods, phase opposition, etc. Finally, all crime series are classified as leading, coincident or lagging with respect to the business cycle.

The rest of the paper is organized as follows. Section 2 describes the data set used; section 3 recalls the DFM methodology, explicating the model used in our framework, whereas in section 4 the results of our application

[1]A static version of DFM was proposed by Stock and Watson (2002).

are shown. Some final remarks will conclude the paper.

2 Data Description

In this section we describe the data set employed in this study. Our data set includes 22 crime types grouped into six macro-groups defined by the Italian National Institute of Statistics (Istat) over the time span 1991:1 up to 2004:12 (monthly data). The groups are: *violent crimes*, *crimes against family and decency*, *property crimes*, *crimes against the economy*, *crimes against the State*, and *other types of crimes*.

Violent crimes includes crimes against the person: assault (ASS), murder (MUR), sex assault (SAS) and involuntary manslaughter (INV). The second group, *crimes against family and decency*, consists of crimes against personal dignity and public morality, like prostitution (PRS) and violation of family support obligations. *Property crimes* is the largest group, and it covers the following crime types: theft (THF), robbery, extortion and kidnapping (REK), damage (DMG), fraud (FRD), embezzlement (EMB), handling (HND) and fraudulent insolvency (FRI). *Crimes against the economy* include, among others, bankrupt (BKR), fraudulent trading (FRT), selling of adulterated foodstuffs (SAF), drug dealing (DRG) and falsity (currency counterfeit (CCN), falsifying documents (FLD) and false seals (FLS)). *Crimes against the State* are composed mainly by crimes against Public Administration and Justice Administration (for example, corruption and irregular administrative acts) and conspiracy crimes. Finally, the last group includes other types of crime (OTC) like smuggling and illegal possession of weapons. The complete list of the types of crimes is shown in Table 0.

The choice of the time span is an important issue in this kind of analysis; in fact, regime changes characterize most Italian crime variables. To be more precise, procedural reforms, depenalizations, law interventions, pardons and reforms of the judiciary can modify data collection and crime definitions, which implies that series might be not homogenous. In the period selected (1991-2004) no substantial reforms were implemented.

The presence of a cyclical component of crime series, could be preliminarily detected from a simple graphical analysis. In the bottom part of Figure 1 we plot the logarithm of the linear detrended series of total crime

(TCR)[2].

Despite the presence of a strong irregular component, it is possible to notice a certain periodic behavior. It is interesting to compare this graph with the analogous series of the Italian GDP, shown in the upper part of Figure 1[3]. The cyclical pattern of GDP is clearer and the turning points could be detected also from a simple graphical inspection; but the two figures show some similar as well as some opposite behavior. In particular, in the period after the end of 1999 the two series show a clear divergent phase; moreover, the large increase in the GDP at the beginning of this period corresponds to an abrupt fall in criminal activity.

This graphical intuition needs to be analyzed in greater depth with appropriate econometric tools. For the reasons reported in Section 1, we decide to perform a DFM.

3 The Dynamic Factor Model

The basic idea of factor models is that all the variables under study are driven by a common non observable factor. In other terms, each variable can be decomposed into a common part and an idiosyncratic noise or short-term component. The purpose of the factor model is to extract the common factor from the full set of variables.

In the non parametric DFM, Forni et al. (2000) consider a vector of n second-order stationary observed variables, call it $\mathbf{z}_t$, which have q orthogonal common factors contained in the vector $\mathbf{y}_t = (y_{1t}, \dots, y_{qt})'$ (in general q is a small number). The multivariate time series $\mathbf{z}_t$ can be decomposed as follows:

$$\mathbf{z}_t = \boldsymbol{\chi}_t^q + \boldsymbol{\varsigma}_t \qquad (1)$$

[2] All the time series used in this work were preliminary seasonally adjusted, using the TRAMO-SEATS routine (Gomez and Maravall, 1997).

[3] The GDP cycle is generally considered a proxy of the cycle of the entire economy. It is available as a quarterly series and it has been transformed into a monthly series using the method proposed in Fernandez (1981).

where $\boldsymbol{\varsigma}_t$ is the $n \times 1$ vector of (cross-correlated) idiosyncratic components, whereas the common part $\boldsymbol{\chi}_t^q$ is a linear projection of $\mathbf{z}_t$ on the space generated by $\mathbf{y}_t$:

$$\boldsymbol{\chi}_t^q = \mathbf{C}_q(L)\mathbf{y}_t \qquad (2)$$

The common factors $\boldsymbol{\chi}_t^q$ and the idiosyncratic components $\boldsymbol{\varsigma}_t$ are hypothesized orthogonal.

As proposed by Forni et al. (2000), the vector χ_t^q can be estimated using the dynamic principal components. In fact, the orthogonality between $\boldsymbol{\chi}_t^q$ and $\boldsymbol{\varsigma}_t$ implies that the spectral density matrix of $\mathbf{z}_t$, $\boldsymbol{\Sigma}(\omega)$, can be decomposed into:

$$\boldsymbol{\Sigma}(\omega) = \boldsymbol{\Sigma}_\chi^q(\omega) + \boldsymbol{\Sigma}_\varsigma(\omega) \qquad (3)$$

where the frequency $\omega \in [-\pi, \pi]$ and $\boldsymbol{\Sigma}_\chi^q(\omega)$ and $\boldsymbol{\Sigma}_\varsigma(\omega)$ are the spectral density matrices of $\boldsymbol{\chi}_t^q$ and $\boldsymbol{\varsigma}_t$, respectively.

Starting from this decomposition, Forni et al. (2000) show that a consistent estimator of $\boldsymbol{\chi}_t^q$ is obtained as the projection of $\mathbf{z}_t$ on the first q eigenvectors of $\boldsymbol{\Sigma}(\omega)$, associated with the first q eigenvalues in descending order. The idiosyncratic part is obtained by difference between $\mathbf{z}_t$ and the estimated $\boldsymbol{\chi}_t^q$.

The estimation of model (1) implies the choice of the number of factors q. A straightforward solution is to select the first q factors explaining a large enough proportion of the series variance. The common factors in $\boldsymbol{\chi}_t^q$ can be considered as the cyclical components of each series contained in $\mathbf{z}_t$.

A nice characteristic of the DFM is the possibility to classify the series as leading, coincident or lagging with respect to a reference series. For example, studying the cycle of crime, one can analyze its behavior with respect to the business cycle. To perform this further analysis we need to calculate the *mean delay* in the first row of matrix $\mathbf{\Sigma}_{\chi}^{q}(\omega)/\omega$; in row terms, the mean delay measures the lags in the movements of a series with respect to another one (see Fiorentini and Planas, 2003). For example, if the mean delay between a crime series and the reference series is equal to 2, it means that the crime series leads the reference series by two periods (or that the reference series lags the crime series by two periods). In general, series showing mean delays between -1 and +1 are considered as coincident; a mean delay higher than 1 implies that the series can be classified as leading (with respect to the reference series), and vice versa for mean delays below -1.

4 Empirical Results

We start our study performing a comparative analysis between the total number of crime offenses, TCR, and the real GDP; in practice, we use a DFM with $n = 2$ and GDP as reference series. This first experiment aims to identify possible links between crime activity and business cycle in Italy, given the considerations derived by the visual analysis of Figure 0. The analysis is performed with the software Busy (Fiorentini and Planas, 2003).

In this bivariate case, the model employs only one common factor. In Table 1 we show the correlations between the two elements of the vector $\boldsymbol{\chi}_t^q$, in particular between the common part of TCR, for several lags and leads, and the common part of GDP. We notice that the maximum correlation is at the same time, but also at lags 1 and -1 (which corresponds to a lead 1) the correlation is more than 0.5 in absolute terms. Moreover, the sign of correlations is always negative (apart lag and lead 6, which are near zero), which is consistent with the idea that, during business cycle expansions, crime level decreases according to the motivation effect (Cantor and Land, 1985), whereas the opposite works during recessions. In terms of mean delay, the model classifies TCR as a lagged variable with respect to GDP, consistently with the theory that criminal agents seem to react with some delay to economic fluctuations.

In Figure 2 we plot the graphs of the common factors, representing the cycles of GDP and TCR respectively. We note that the cyclical behavior of total crime is not so clear and it is difficult to compare it with the economic fluctuations shown by GDP. Anyway a degree of counter-cyclical behavior can be observed, especially in the final part of the time series.

To sum up these first results, the behavior of the aggregate variable TCR, with respect to GDP, is not so clear and its classification remains uncertain because the indications of Table 1 and the mean delay criterion seem to differ; on the other side, the visual inspection of the cyclical behavior of the two variables does not favor intuitive interpretations.

Obviously, total crime puts together a number of heterogeneous crimes. Using aggregate categorical data, we may incur in two types of errors: on the one hand, aggregate data may show a weak relationship to the economic cycle as they incorporate types of crime with opposite behaviors; on the other hand, it is possible to expect that some criminal activities could be ahead of economic phases while other crime types exhibit a time delay.

As a matter of fact, it can be interesting to divide total crime by crime type and evaluate the relationship between each crime subgroup and business cycle. All variables under study have been transformed in the same way described in section 2: natural logarithmic transformation, to avoid all cases in which the series variance increases with the mean, and linear detrending, in order to obtain second-order stationary series.

Twenty-two crime variables along with real GDP series (the reference variable) are employed. The procedure is performed in two steps: firstly, the common part is extracted by the series, while in the second stage all variables are classified according to their temporal relationship with the reference series. This way, we can define whether a specific type of crime is coincident, leading or lagging respect to *GDP* series.

We require that the number of factors identified explain close to 50% of the total variance; in this first running the number of factors selected is three. The second column of table 2 shows the highest value of cross-correlation between each crime variable and GDP with the associated lags in parenthesis, the third one indicates the ratio of the common component variance over series variance, while the fourth and fifth columns present the classification status of each series in terms of phase (opposition or not) and leading, coincident or lagging behavior respectively. Unfortunately, most of the series are weakly correlated with the reference variable. Such low correlation could indicate strong idiosyncratic behavior for these variables. Hence, the crime type with the lowest correlation coefficient is eliminated and we re-estimate DFM. We reiterate such procedure until all remaining variables have a high correlation with respect to the reference series and the ratio between the variance of the common component and the variance of the series is sufficiently high. The choice of a threshold value for correlation and for the variance ratio, to select series with a strong relationship with the reference series, is quite subjective. Fiorentini and Planas (2003) indicate a threshold value for correlation, in absolute terms, equal to 0.4; for the variance ratio, We can suppose that a series has a strong common component if it explains almost 60% of its variance (so that the idiosyncratic part accounts for less than 40%).

Following this procedure, we select seven types of illegal activity, using two factors, illustrated in Table 3: crimes against the State (AGS), bankruptcy (BKR), embezzlement (EMB), false seals (FLS), fraud (FRD), fraudulent trading (FRI), involuntary manslaughter (INV). As shown in the second column of table 3, all correlation coefficients are above $|0.4|$, varying between -0.48 of FRI and the very high value -0.96 of FRD. Furthermore, the ratio of common component variance over series variance is presented in the third column of table 3, showing how this component explains a large part of the variance of AGS; in the worst case, relative to BKR, it explains 62% of the total variance. This selection can be considered as a set of crime types with cyclical behavior, which has a strong relationship with the business cycle. We emphasize that no violent crime is included in the last output: such a result is in line with other empirical studies that find a low correlation between violent crimes and economic performance (Cook and Zarkin, 1985; Fougère et al. 2007).

In Figure 2 we show the graphs of each element of $\boldsymbol{\chi}_t^2$, for each one overlapping the first element of the vector, constituted by the cycle of GDP. Notably, all crime variables, except for INV, exhibit a countercyclical behavior with respect to GDP (this can be seen also in the fourth column of Table 3), i.e. we observe an increase of such criminal offenses during recessions . This is particularly evident after 1999, when GDP shows a clear growth until the end of 2000 and subsequently a long recession until June 2003; the behavior of the other cycles is opposite (apart from INV, which has no divergent phase). Notice also as the cyclical signal of these types of crime is clearer with respect to the one of the total crime, analyzed in Figure 2.

Now, let us comment more in detail the different classification of the seven crime types. Involuntary manslaughter is largely composed by road and work related deaths. Hence, during expansions, employment rate and road traffic increase and we expect a rise of accidents and victims. To confirm this hypothesis, we observe that INV is classified as a coincident series (last column of table 3).

Bankruptcy, embezzlement, fraudolent insolvency, crimes against the State seem to be leading series: they have been observed to move at an earlier date with respect to the reference series. Although at first glance this seems to be a little bit puzzling, it does actually make sense. As recently investigated by many scholars, the causal relationship between crime and economy can be bidirectional. For instance, recently Detotto and Otranto (2010) show some evidence about the negative influence of criminal activity on the economic performance, using a state space model for the Italian GDP. The first three types of illegal activity (BKR, EMB and FRI) are typically corporate crimes that can lead to negative spillover effect. Crime against the State is mostly made up of corruption offenses, which reduce the efficiency of Public Administration. Such negative effects can drive the whole economy down. Furthermore, Delli Gatti et al. (2009) theorize a model in which the network connections among agents can amplify the impact of individual bankruptcy on the business cycle. T

Another possible interpretation is consistent with the idea that, in the recent history of recessions, real crises are preceded by financial crises; for example, the beginning of the latest recession has been established by NBER in December 2007 for the real economy, but the financial crises had started in July 2007; the 2001 recession, included in our data set, followed the collapse of the Dot-com bubble of March 2000. It is reasonable to expect that during financial crises the financial crimes could experience an increase, so their cycle is leading with respect to the business cycle.

Finally, fraud and false seals are classified as lagging variables. Fraud is a way to make immediate monetary gain. False seals (FLS) refers to marks or signs counterfeiting, which is mainly linked to illegal sales and frauds. It is reasonable to expect that such crimes could respond to economic fluctuations. Precisely, we see that these crimes rise during recessions, and drop during expansions.

5 Remarks

In this paper we have started from the idea that crime follows a cycle, which could be linked to the business cycle. In order to verify this hypothesis we have analyzed several types of Italian crime using a DFM to extract a common cycle with respect to GDP series, taken as a proxy of the business cycle of the whole economy.

In a first step, we compare total crime with GDP series in order to identify possible links between crime activity and business cycle in Italy. The common component of TCR and GDP are negatively correlated: a rise in the economic performance is associated with a decrease in total crime rate. Furthermore, the model classifies TCR as a lagged variable with respect to GDP, in line with the theory that crime reacts with some delay to economic fluctuations.

In a further step, we divide the total crime rate in 22 crime types and rerun the dynamic factor model. We find that seven crime types have a strong link with GDP.

Notably, all crime variables, except for involuntary manslaughter, show a countercyclical behavior with respect to GDP. The involuntary manslaughter group includes road and work related deaths, so it is reasonable to expect that during expansions the number of accidents and victims rise along with the employment rate and road traffic.

An important novelty in this nonparametric approach is the fact that we can detect if the cyclical component of the crime series lags, leads or coincides with the cyclical one of GDP; we detect four series with a leading behavior, two lagging types and only one coincident series. Most of the previous studies focus on the assumption that the business cycles causes, or interacts with, crime fluctuations, and not vice versa. Our results are not in contrast with this theory, in the sense that we do not study the cause-effect relationship between crime and economic fluctuations; the main result of our study is that only some kinds of crime are linked to the business cycle and that leading series probably do not cause the economic business cycle, but are dependent on other economic causes, such as the crisis of financial markets, often leading with respect to the business cycle.

Future work could addresss the relationships between the crime cycle and other economic variables, such as financial variables (volatility of markets, speculative bubbles, etc.), unemployment, migration movements, etc.

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Tables

Table 1: Istat classification of crime typologies

Crime group	Crime typology	Code
Violent crimes	Assault	ASS
	Involuntary manslaughter	INV
	Murder	MUR
	Sexual assault	SAS
Crimes against family and decency	Crime against the family	AGF
	Prostitution	PRS
Property crimes	Damage	DMG
	Embezzlement	EMB
	Fraud	FRD
	Fraudulent insolving	FRI
	Handling	HND
	Robbery, extortion and kidnapping	REK
	Theft	THF
Crimes against the economy	Bankrupt	BKR
	Currency counterfeit	CCN
	Drug dealing	DRG
	Falsifying documents	FLD
	False seals	FLS
	Fraudulent trading	FRT
	Selling adulterated foodstuffs	SAF
Crime against the State		AGS
Other types of crimes		OTC

Table 2: Correlation between common parts of total crime series (for several lags and leads) and GDP

Lags												
-6	-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5	+6
0.01	-0.10	-0.23	-0.36	-0.49	-0.59	-0.64	-0.50	-0.37	-0.23	-0.11	-0.01	0.05

Table 3: Analysis of the common parts of crime categories series and GDP

Series name	Common parts correlation* (lags)	Ratio common component variance**	Phase classification	Series classification
AGF	0.16 (-2)	0.61	(+)	Lagging
AGS	-0.18 (-1)	0.68	(-)	Lagging
ASS	0.13 (-2)	0.70	(+)	Lagging
BKR	-0.68 (0)	0.59	(-)	Leading
CCN	-0.08 (-4)	0.53	(-)	Lagging
DMG	-0.42 (0)	0.59	(-)	Lagging
DRG	0.41 (-1)	0.39	(+)	Leading
EMB	-0.81 (0)	0.78	(-)	Leading
FLD	0.06 (-3)	0.53	(-)	Lagging
FLS	-0.63 (0)	0.72	(-)	Lagging
FRD	-0.85 (0)	0.56	(-)	Lagging
FRI	-0.62 (0)	0.69	(-)	Lagging
HND	0.13 (-3)	0.56	(-)	Lagging
INV	0.56 (-1)	0.54	(+)	Coincident
MUR	0.37 (0)	0.54	(+)	Coincident
OTC	-0.42 (0)	0.33	(-)	Lagging
PRS	-0.80 (0)	0.44	(-)	Lagging
REK	0.15 (-4)	0.47	(+)	Lagging
SAF	-0.30 (0)	0.45	(-)	Lagging
SAS	0.16 (-2)	0.79	(+)	Lagging
SFR	-0.80 (0)	0.44	(-)	Lagging
THF	-0.18 (0)	0.68	(-)	Lagging

Notes: (*) Highest cross-correlation between common parts of series and reference series; (**) Ratio common component variance over series variance; (+) and (-) indicate the crime common component is in phase and in phase opposition respectively with respect to the common component of the GDP.

Table 4: Analysis of the common parts of crime categories series and GDP

Series name	Common parts correlation* (lags)	Ratio common component variance**	Phase classification	Series Classification
AGS	-0.78 (0)	0.85	(-)	Leading
BKR	-0.67 (0)	0.62	(-)	Leading
EMB	-0.80 (0)	0.77	(-)	Leading
FLS	-0.64 (0)	0.71	(-)	Lagging
FRD	-0.96 (0)	0.68	(-)	Lagging
FRI	-0.48 (0)	0.78	(-)	Leading
INV	+0.64 (0)	0.77	(+)	Coincident

Notes: (*) Highest cross-correlation between common parts of series and reference series; (**) Ratio common component variance over series variance; (+) and (-) indicate the crime common component is in phase and in phase opposition respectively with respect to the common component of the GDP.

Figures

Figure 1: Linear detrended series of GDP (upper graph) and total crime (bottom graph) in Italy

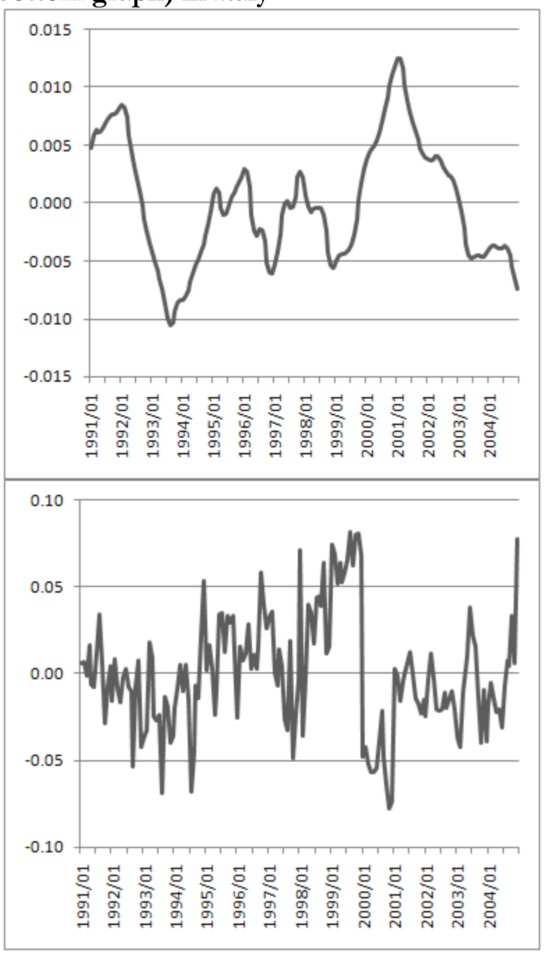


Figure 2: Cyclical components of GDP (gray line) and TCR (black line)

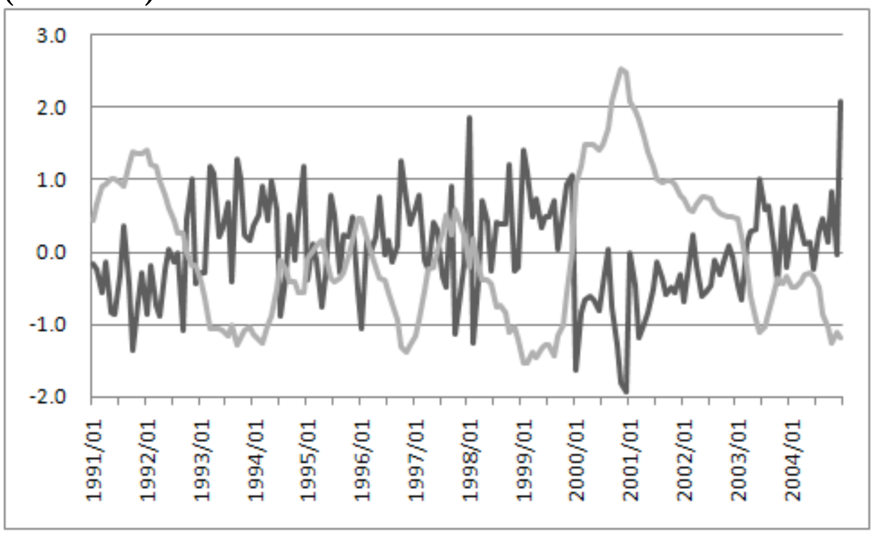
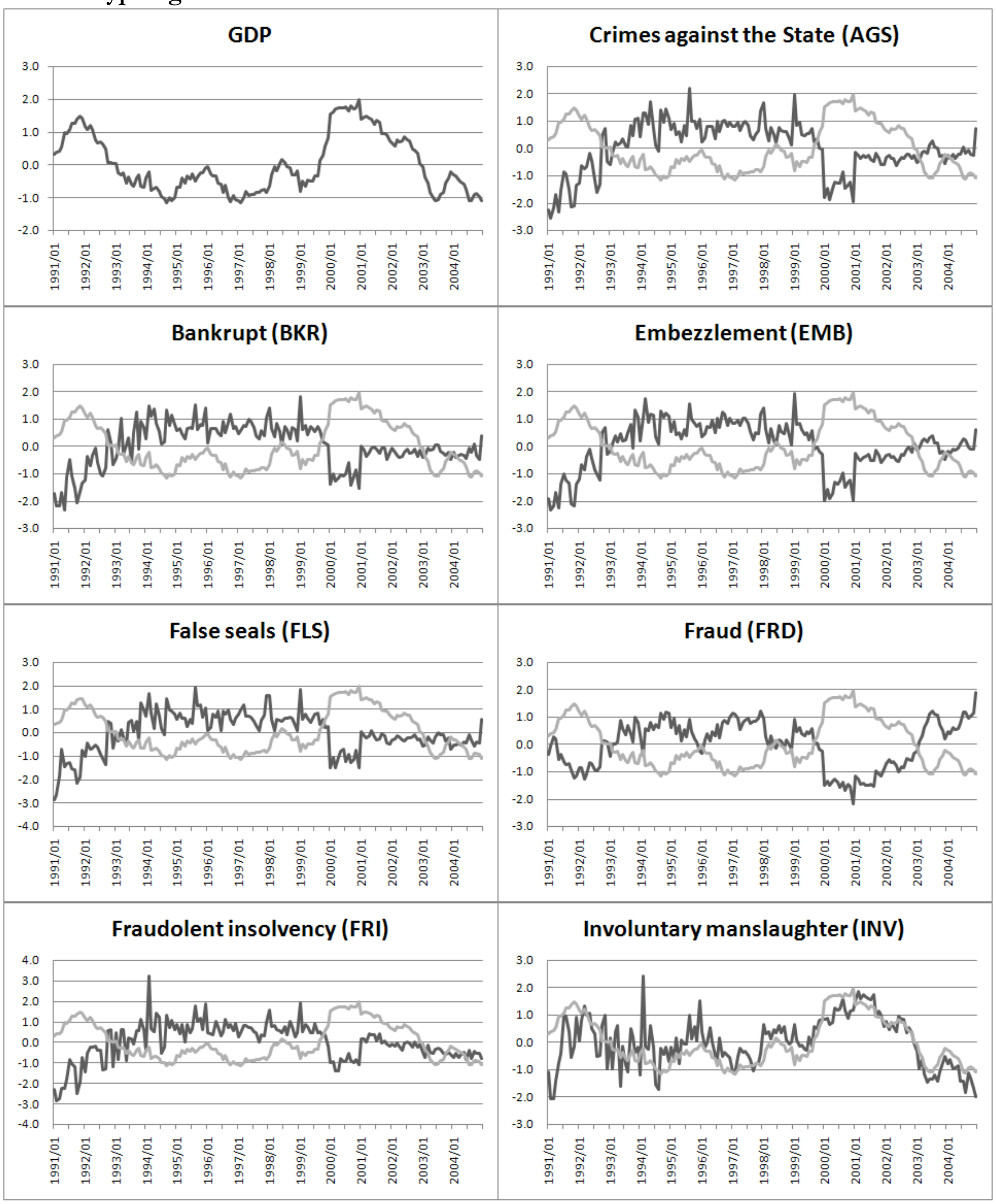


Figure 3: Cyclical components of GDP (gray line) and selected typologies of crime



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