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CYCLES IN CRIME AND ECONOMY REVISED

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Cycles in Crime and Economy Revised*

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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, but this causal effect is observed only for some typology of crimes, such as property crimes. In this work we examine the possibility of the existence of some common factors (interpreted as cyclical components) driving the dynamics of Gross Domestic Product and a large set of criminal types by using the nonparametric version of the dynamic factor model. A first aim of this exercise is to detect some comovements between the business cycle and the cyclical component of some typologies of crime, which could evidence some relationships between these variables; a second purpose is to select which crime types are related to the business cycle and if they are leading, coincident or lagging. Italy is the case study for the time span 1991:1 - 2004:12; the crime typologies are constituted by the 22 official categories classified by the Italian National Statistical Institute. The study finds that most of the crime types show a counter-cyclical behavior with respect to the overall economic performance, and 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 the 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 behaviors 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.

Most of the studies show some empirical evidences of the presence of the relationship between crime and business cycle for specific categories of crimes. 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 crimes can be indirectly 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. Pyle and Deadman (1994) analyze via error correction models the long-run relationships between crime variables (burglary, theft and robbery) and each of the three variables personal consumption, GDP and unemployment in post-war England and Wales. Later, Hale (1998) replicates the analysis of Pyle and Deadman (1994) and he finds that personal consumption has a long-run and short-run relationship with property crimes, while unemployment plays a role only in explaining short-run crime variations. 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). Recently, by using annual panel data, Arvanites and Defina (2006) show that an improving economy reduces property crimes. Building on the theoretical foundation provided by Becker (1968), recent works try to explain the previous empirical evidences (Cantor and Land, 1985; Box, 1987; Greenberg, 2001); in our view, an interesting idea is proposed by Field (1990). Although his analysis is mainly devoted to explore the connection between property-personal crimes and business cycle in second post-war England and Wales, his interpretation seems to have a general value for many crime typologies. Field (1990) identifies three possible relationships between crimes and economic variables:

1. crime affects business cycle;

2. crime and business cycle are mutually driven by a hidden factor;

3. business cycle affects crime.

Although Field (1990) indicates the third statement as the only possible one, we are strongly convinced that all three options can be realized. Firstly, it is possible that some specific criminal activity presents a dynamics which seems to have a leading behavior with respect to the business cycle. Just, as a deceleration in specific sectors of the economy may spread to other related sectors and the whole economic production (for example, financial crisis may be preliminary to global economic crises), so specific economic crimes occurring in one sector of the economy could produce an economic downturn. Recently, by applying a time varying approach to the Italian case, Detotto and Otranto (2010) find that crime levels can affect GDP growth. Secondly, exogenous shocks, like for instance technological improvements, could have a double effect: on the one hand they may drive the economic growth, on the other hand they may create new windows of opportunity for criminals (Taylor, 2002).

The above mentioned considerations underline (implicitly) that a crucial task is the choice of the variable appointed to represent the business cycle. In general, the empirical literature on crime has used measures of unemployment, wages, consumption, etc. Such variables can not fully represent the whole economy but they are strictly related to a social discomfort. Furthermore, the business cycle is a composite element consisting of several economic variables, which have different behavior with respect to labour market. To be more precise, the labour market is often lagged with respect to the business cycle (Field, 1990; Forni et al., 2001). In our opinion, it is preferable to use a variable which is more correlated with all the economic variables (see Forni et al., 2001); a natural choice falls on the Gross Domestic Product (GDP), largely used as a proxy of the business cycle (CEPR, 2009).

Moreover, if the hypothesis of the crime-business cycle relationship is verified, we should observe that both their dynamics follow a common component, maybe with some lags or leads. In this case the extraction of a common component could help to examine the existence and the sign (pro or counter cyclical) of such relationship, and the presence of a cycle in the illegal activities.

The possibility of pro-cyclical or counter-cyclical behaviors between crime and business cycle is well explained in Cantor and Land (1985), who theorize the macroeconomic relationship between the economic performance and criminal activity. They indicate two opposite strands of incentives to criminal behavior: motivation effect and opportunity effect. The former refers to the incentive to commit crime stemming 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. Field (1990) links also the negative correlations to the motivation effect and the positive correlation to opportunity effects, but, in his empirical analysis, the negative motivation effect seems be dominant in the short term. Moreover, among the positive effects, he identifies also the ”routine activity” (see, for example, Cohen and Felson, 1979): when people have high availability of money, they spend more time away from their homes to consume; this situation increases chances that people and property are exposed to crime. It is worth noting that the impact of opportunity and motivational effect can be different depending on the crime typology under study. For instance, involuntary manslaughters seem to be more related to routine activities so that we expect a positive correlation with economic performance, whereas property crimes can be more affected by motivation effects that imply a negative correlation with the economic fluctuations.

In this framework, the availability and the nature of the data are critical in order to perform the empirical analysis and to verify the theoretical foundations. In a dynamic framework, such the analysis of the economy-crime relationship, it is obvious that the longitudinal data are preferable over the cross-sectional ones. Furthermore, the use of aggregate data could fail to highlight the presence of differences among macro-groups of crime because they are the sum of several typologies with different cyclical behavior. Moreover, the bulk of research done in this area examines the relationship between the business cycle and crime using annual data. In time series modeling, the frequency of time series is a crucial factor to obtain robust and efficient results and to give stronger empirical evidence of leading or lagging infra-annual movements among the variables in use. Also, as we will show in the present paper, the pro-cyclical and counter-cyclical dynamics could alternate each other along time, and this is quite evident using monthly or quarterly rather than annual data.

In order to analyze the cyclical component of a large number of crime types and the relationship between illegal activities and business fluctuations, we suggest the use of the non parametric Dynamic Factor Model (DFM), proposed by Forni et al. (2000).[1] This approach has been successfully used in several economic analyse; 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

[1]A static version of DFM was proposed by Stock and Watson (2002). For the parametric DFM see Sargent and Sims (1977) and Stock and Watson (1993)

element, cleaning each variable from its idiosyncratic components.

For our analysis the choice of this approach presents several advantages with respect to other more common multivariate time series models, such as Vector AutoRegression (VAR) or Vector Error Correction models. First of all, we deal with a large number of crime typologies; in general, parametric models are not able to work with large dimensions because of the high number of parameters to be estimated and because of computational problems (see, for example, the discussion in Bauwens et al., 2006, about such problems in the analysis of multivariate financial time series, which typically involves a large number of time series). The nonparametric DFM does not suffer from such problems because it is based on the spectral decomposition of the density matrix (some technical details are given in section 3). Second, in general the hypothesis of Normal distribution of the variables under study is assumed true in multivariate parametric models, but the crime series rarely follow this distribution Third, the nonparametric DFM version proposed by Forni et al. (2000) is based on a dynamic principal component analysis, which is more suitable in a time series framework then a classical principal component approach. In fact, the dynamic principal components are obtained applying a bilateral filter to the common factors of the variables under study; in this way we can consider a combination of present, past and future observations of these factors for each time t, establishing a dynamic structure in the weighted sum of factors, which can be interpreted as the cycle of the variable. Finally, it is possible to evaluate the behavior of each series with respect to a reference series; choosing GDP as reference series, a by-product of the Forni et al. (2000) procedure provides the automatic classification of each typology of crime in terms of their behavior with respect to the business cycle (pro and counter cyclical, leading, coincident or lagging) and the possibility to obtain a synthetic indicator of the comovements of the series.

In this work we apply the nonparametric DFM to 22 crime types in Italy in the period 1991-2004, using monthly and quarterly data. The main purpose is threefold. First, we check for the presence of a cyclical component among the crime variables under study. Second, we perform a comparison between crime and economic fluctuations, in order 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. It is worth noting that we do not study factors and determinants of the illegal activities, but only the presence of comovements with the business cycle without checking any causal relationships.

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 are shown, starting from the series of total crimes, then using six groups of crimes classified by the Italian National Statistical Institute (Istat) and finally considering all 22 typologies. The main analysis is based on monthly data, but we will comment briefly also the results relative to quarterly data, showing a high degree of robustness of the results. Moreover, given the particular interest of the economic literature on the analysis of street crimes, another subsection will consider the cyclical behavior of this specific subset. 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 Istat, available over the time span 1979:1 up to 2004:12 (monthly data). The groups are: *crimes against person* (CAP), *crimes against family and decency* (CFD), *property crimes* (PCR), *crimes against the economy* (CAE), *crimes against Public Administration* (CPA), and *other types of crimes* (OTC).

Crimes against person are composed by: namely assault (ASS), murder (MUR), sex assault (SAS), and involuntary manslaughter (INV). Precisely, INV is largely composed by traffic fatalities and work-related deaths. The second group, *crimes against family and decency*, includes 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 typologies: theft (THF), robbery, extortion and kidnapping (REK), property damage (DMG) [2], fraud (FRD), embezzlement (EMB), handling (HND) and fraudulent insolvency (FRI) [3]. *Crimes against the economy* include, among others, bankrupt (BKR), fraudulent trading (FRT), selling of adulterated foodstuffs (SAF) [4], drug dealing (DRG) and falsity (currency counterfeit (CCN), falsifying documents (FLD) and false seals (FLS). *Crimes against the Public Administration* are composed mainly by crimes against national and local Public Administration (for example, corruption and irregular administrative acts), along with 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 1.

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. For this reason we have decided, in our analysis, to select the series only for the period 1991-2004, when no substantial reforms were implemented. All series refer to crimes reported to the police, which represent the tip of the iceberg of criminal phenomena. Unfortunately, victimization surveys are not available for all type of crimes and for all the period under study. To date, only two victimization surveys were made by Istat in Italy (in 1997 and 2002) and the propensity to report crime is quite similar between the two surveys (Istat, 2004). So, we expect, given also the relatively short period under study, that the propensity of people to report crime to the police has little variance in the time span 1991-2004.

In Table 2 the main descriptive statistics are shown; notably, all the selected illegal activities do not present zero values. Only SAF presents some cases with a small number of events (at least 2), but also a large variability with respect to the other typologies. Fur-

[2] It is important to note that in Italy, unlike the United States, such crime does not include intentional damages, like vandalism.

[3] This form of illegal activity is generally associated with false accounting by managers in order to divert resources for personal use and gain.

[4] SAF offences are connected with the sales of adulterated foodstuffs. They include any undesirable adulteration in foodstuffs or reduction or extraction of any natural quality or utility from foodstuffs in order to maintain health and convenience of the general public.

thermore, it is important to notice that most of the criminal typologies are not Normally distributed, that implies some difficulties in the implementation of the parametric models. Finally, column 2 of Table 2 shows that 60% of total crime is composed by thefts and that the assaults are the 94% of the crimes against persons. The Italian crime classification does not consider explicitly the category of street crimes, which is very relevant in the crime analysis; we can collect it putting together ASS, MUR, SAS, REK and THF, which is, on average, the 70% of total crimes.

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 $\boldsymbol{z}_t$, which have q orthogonal common factors contained in the vector $\boldsymbol{y}_t = (y_{1t}, \ldots, y_{qt})'$ (in general q is a small number). For example, in our framework, $\boldsymbol{z}_t$ could be a (7×1) vector containing the GDP and the six groups of crimes, described in the previous section, at time t, whereas $\boldsymbol{y}_t$ is a vector of unobservable common factors for the seven variables contained in $\boldsymbol{z}_t$.

The multivariate time series $\boldsymbol{z}_t$ can be decomposed as follows:

$$\boldsymbol{z}_t = \boldsymbol{\chi}_t^q + \boldsymbol{\varsigma}_t \tag{3.1}$$

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 $\boldsymbol{z}_t$ on the space generated by $\boldsymbol{y}_t$:

$$\boldsymbol{\chi}_t^q = \boldsymbol{C}_q(L)\boldsymbol{y}_t \tag{3.2}$$

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

The term *idiosyncratic*, commonly used in this kind of modeling, could be a bit misleading, especially in our framework. It would imply that the causes of specific crimes, aside from GDP, are specific to each crime, whereas it is likely that $\boldsymbol{\varsigma}_t$ in (3.1) might be related to some set of omitted variables. Anyway, it is important to note that we do not need any hypotheses about the so-called idiosyncratic components, so that they could be also autocorrelated and correlated among them, or also dependent on specific other variables. What the nonparametric DFM does is capturing the common movements of the series contained in $\boldsymbol{z}_t$ without analyzing some cause-effect relationships among variables. If someone is interested also in explaining the relationships among economic and crime variables, it would be necessary to hypothesize some parametric model, but, for our purpose, which is capturing the cycles of types of crime linked to business cycle, the nonparametric DFM is an ideal choice. Having that in mind, we will maintain the term *idiosyncratic* for the non common part of (3.1).

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 ς_t implies that the spectral density matrix of $\boldsymbol{z}_t$, $\boldsymbol{\Sigma}(\omega)$, can be decomposed into:

$$\boldsymbol{\Sigma}(\omega) = \boldsymbol{\Sigma}_\chi^q(\omega) + \boldsymbol{\Sigma}_\varsigma(\omega) \tag{3.3}$$

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 ς_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 $\boldsymbol{z}_t$ on the first q eigenvectors of $\Sigma(\omega)$, associated with the first q eigenvalues in descending order. The idiosyncratic part is obtained by the difference between $\boldsymbol{z}_t$ and the estimated $\boldsymbol{\chi}_t^q$.

We refer to Forni et al. (2000) and (2001) for technical details. What we want to underline here is that the DFM uses the extension of the principal component to the time series case (Brillinger, 1981), where it is possible to have some leading, lagging or coincident behaviors. In practice, this is made extracting the dynamic principal components, which are related to the eigenvalues and eigenvectors of the spectral density matrix, and not of the covariance matrix, as in the static (classical) case. In other words, we compute the spectral density matrix $\boldsymbol{\Sigma}(\omega)$ at different frequencies ω,[5] then we compute the first q eigenvalues and eigenvectors for each $\boldsymbol{\Sigma}(\omega)$, combining them to obtain the estimation of $\boldsymbol{y}_t$ and $\boldsymbol{C}_q(L)$ in (3.2), as described in Forni et al. (2000). This way, the common components $\boldsymbol{\chi}_t^q$ in equation (3.2) are obtained as a linear combination of lagged, coincident and leading factors $\boldsymbol{y}_t$. For example, if we consider the $j-th$ variable of the vector $\boldsymbol{z}_t$ and we have identified 2 factors, y_{1t} and y_{2t}, the common component is loaded as:

$$\chi_t^{2,j} = \sum_{i=-m}^{m} c_{1,i}^j y_{1,t-i} + \sum_{i=-m}^{m} c_{2,i}^j y_{2,t-i} \tag{3.4}$$

where $\chi_t^{2,j}$ is the cyclical component of the $j-th$ variable, $c_{1,i}^j$ and $c_{2,i}^j$ $(i = -m, \ldots, m)$ are weights for the variable j estimated from the Forni et al. (2000) procedure. This way each variable in $\boldsymbol{z}_t$ will load the common factors in a specific way. Notice that the case of static principal components is obtained as a particular case of (3.4) with $m = 0$.

The estimation of model (3.1) 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. Typical thresholds would be between 50% and 70%. The common factors in $\boldsymbol{\chi}_t^q$ can be considered as the cyclical components of each series contained in $\boldsymbol{z}_t$.

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. In this case we have to consider the cyclical component of GDP, contained in the vector $\boldsymbol{\chi}_t^q$, and to compare all the other elements of this vector, each one representing the cyclical components of each crime types, with the cycle of GDP. To perform this further analysis we need to calculate the *mean delay* in the first row of matrix $\boldsymbol{\Sigma}_\chi^q(\omega)/\omega$; in row terms, the mean

[5] We use $(2m+1)$ values for ω, with $\omega_k = 1 - \frac{|k|}{m+1}$, with $k = -m, \ldots, m$ and $m = round(\frac{sqrtT}{4})$, as suggested in Forni et al.(2000).

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

Our study is composed by four steps. We start the analysis performing a bivariate DFM on the total number of crime offenses 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 above mentioned considerations derived by the visual analysis of Figure 1. We then perform a first level of disaggregation, comparing the cycle of GDP with the 6 groups indicated by Istat, and recalled in Section 2. Third, we further disaggregate our dataset into 22 typologies of crimes, as described in Section 2. These sequential steps evidence that the crime-GDP comovements are not common to all the crime types but only to a small subgroups of them. In order to check the robustness of our findings, we replicate the analysis with quarterly data. Finally, we focus on street crimes, a specific crime subgroup whose relationship with the business cycle have already been analysed in the economic literature, as underlined in the Introduction. Notably, such subset does not show a common behavior with respect to business cycle; in the last subsection, we will try to analyze its cyclical component in order to investigate the causes of its low correlation with the business cycle.

The three previous analyses are made using monthly data; the GDP is available as a quarterly series and it has been transformed into a monthly series using the method proposed by Fernandez (1981). This operation would preserve the large information about crimes, which is a desirable property in statistical modeling, in particular in a time series framework. In spite of some contributions in multivariate modeling of business cycle with both quarterly and monthly data (Mariano and Murasawa, 2003, Otranto, 2005), actually this topic is not diffused in the econometric analysis, and many authors adopt the Fernandez (1981) transformation to obtain monthly data from quarterly observations (for the Italian GDP, see Altissimo et al., 2000, and Bruno and Otranto, 2008).

All the time series used in this work were preliminarily seasonally adjusted, using the TRAMO-SEATS routine (Gomez and Maravall, 1997). As said in the previous section, the DFM is based on series of stationary observed data. We have transformed all the seasonally adjusted series into logarithms and then we have linearly detrended them. The transformed series were subject to the Phillips and Perron (1988) test for stationarity, obtaining evidence for stationarity for all the series at a significance level of 5%.[6]

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

[6]To save space we do not show these results, that are available on request.

of crime is coincident, leading or lagging respect to GDP series. The estimation and the extraction of the common components is performed with the software Busy (Fiorentini and Planas, 2003).

4.1 Total crime and GDP

Starting from the bivariate case with GDP and the total number of crime offenses (TCR), the presence of a cyclical component of crime series and its relationship with the business cycle could be preliminarily detected from a simple graphical analysis. In Figure 1 we plot the logarithm of the linear detrended series of TCR and of the GDP; the time series TCR presents a strong irregular component, so we have smoothed it with a 7-terms moving average. The two series show very similar fluctuations, and they seem to be procyclicaI until the third peak of GDP (September 1995) and countercyclical from that date onwards. The correlation coefficient for the full time span between the log-detrended GDP and TCR is equal to -0.21; if we split the dataset into three parts using September 1995 and December 2000 as breakpoints, the correlation is equal to 0.39 in the first span, -0.73 in the second one, and -0.17 in the last one. Remarkably, at the beginning of the 2000s a large increase in the GDP corresponds to an abrupt fall in criminal activity. Such behavior could create some problems in the estimation of a common component for the full period; keeping in mind these possible limitations, we estimate a DFM for this bivariate case.

The model (3.1)-(3.2) has a very simple form, employing only one common factor:

$$\begin{bmatrix} GDP_t \\ TCR_t \end{bmatrix} = \begin{bmatrix} \chi_t^{1,GDP} \\ \chi_t^{1,TCR} \end{bmatrix} + \begin{bmatrix} \varsigma_t^{GDP} \\ \varsigma_t^{TCR} \end{bmatrix}$$

$$\begin{bmatrix} \chi_t^{1,GDP} \\ \chi_t^{1,TCR} \end{bmatrix} = \begin{bmatrix} \sum_{i=-m}^{m} c_i^{GDP} y_{t-i} \\ \sum_{i=-m}^{m} c_i^{TCR} y_{t-i} \end{bmatrix}$$

In Table 3 we show the correlations between the two elements of the vector χ_t^1, in particular between the common part of TCR, for several lags and leads, and the common part of GDP.[7] 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 close to zero), which is consistent with the idea that, during business cycle expansions, crime level decreases, whereas the opposite works during recessions. This behavior seems to be in line with the theory of the motivation effect (Cantor and Land, 1985); unfortunately, the DFM is not able to discern between the motivation and opportunity effects described in section 1. Interestingly, this result could be given by the sum of motivation and opportunity effect, where the former exceeds the latter. [8]

The mean delay is equal to -1.8; on average, changes in business cycle drive crime activity about 2 months later. As a matter of fact, TCR is a lagged variable with respect to GDP, consistently with the theory that criminal agents react with some delay to economic fluctuations. Such output seems to be confirmed also by the visual inspection of Figure

[7] Correlations from lag (lead) 6 to 12 are less than 0.01, so, to save space, we do not report them.

[8] We are in debt to an anonymous referee for this interpretation.

2 which represents the common factors, that is, the cycles of GDP and TCR respectively. Notice that we find the same results if we use quarterly data. This common component is more strongly related to GDP than to TCR; in fact, it explains 77.4% of the variance of GDP and 58.8% of the variance of the crime variable, with a correlation between both common components equal to -0.64. In other words, the findings seem to confirm the counter-cyclical and lagged behavior evidenced in the right side of Figure 1.

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 phase behaviors (procyclical vs counter-cyclical); on the other hand, we might expect that some criminal activities could exhibit different time delays (leading, coincident and lagging behaviours).

As a matter of fact, it can be interesting to disaggregate total crime and study the relationship between each crime group and/or type and business cycle.

4.2 Crime groups and GDP

A first level of detail is obtained considering the six groups of crimes identified by Istat (Table 1), that, along with GDP, involve a 7-variate DFM. By setting the minimum explained variance to 0.60, the number of factors selected is equal to two, as in the example shown in equation (3.4).

The correlation coefficients between the common parts of the crime groups and GDP are shown in Table 4; we can notice that the maximum correlation is achieved at lag 0 for all series, with negative sign and an asymmetric decay toward zero. In more detail, both OTC and PCR groups show a higher persistence in the correlation for negative lags, whereas CAE, CFD and CPA show higher correlations for positive lags. We note that such behavior is consistent with the classification, based on the mean delay, in leading and lagging status. The only exception is represented by the group CAP, which in general exhibits low correlation with GDP common component (the maximum is in correspondence of lag -3, equal to 0.21) and especially for positive lags (all less than 0.1).

Table 5 indicates that the variance explained by the common component is more than 70% for CPA and CAE, whereas PRC does not exhibit a common cyclical component (it explains only 36.6% of its variance). In order to select which variables have a significant common component, we fix a threshold value for the explained variance (60%) and for the correlation (in absolute value) between the common components of crime variables and GDP (0.4).[9] The selected variables are OTC (classified as lagged variable with respect to GDP), CAE and CPA (leading variables with respect to GDP).

It could be a bit surprising that property crimes, mostly street crimes like thefts and robberies, are not correlated to business cycle. A possible explanation might be that this group contains several typologies of crimes with different behaviors with respect to the business cycle causing a sort of compensation effect across the series. In other word, it could be possible that two series belonging to the same group have an opposite behavior with respect to GDP (i.e. leading and lagging status or procyclical and countercyclical)

[9]Such choice of a threshold value for the common component correlations and for the variance ratio is quite subjective. The values used here are proposed by Fiorentini and Planas (2003).

and their aggregate effect is annihilated. For what concerns CAP, the findings are in line with the economic literature (see for instance Cook and Zarkin, 1985) where no relationship is found between personal crime and economic changes. Moreover, the results of the last analysis could depend mainly on some types of crime, which, being more frequent than others, are likely to dominate the cyclical component of the groups under study. For these reasons, in a further step a deeper analysis is conducted in order to identify which typologies of crime are the most closely related to the business cycle.

4.3 Crime types and GDP

In this subsection, we focus on the analysis of twenty-two crime variables, along with real GDP series. We require the selected factors to explain at least 60% of the total variance.[10]

Table 6 presents the output of the estimated DFM with three identified factors. The second column of Table 6 shows the highest value of cross-correlation between each crime variable and GDP, and the associated lags in parenthesis; the third column indicates the ratio of the common component variance over series variance, and the contribution of each factor, while the fourth and fifth ones contain 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 to the reference variable. In order to select the crime variables which have high correlation and similar cyclical behavior with respect to GDP, we propose a simple algorithm to select the series under study; it is formed by the following steps:

1. eliminate the crime typology associated with the lowest correlation coefficient and re-estimate the DFM with the remaining variables;

2. if the correlation coefficient, in absolute value, is less than 0.4, then go to step 1. Continue until all the correlation coefficients are higher, in absolute value, than 0.4;

3. eliminate the crime typology associated with the lowest ratio between the variance of the common component and the variance of the series (if less than 60%), and re-estimate the DFM with the remaining variables;

4. if the ratio value is less than 60%, then go to step 3. Continue until all the ratios are higher than 60%;

Following such procedure, seven types of illegal activities and two factors are selected, as illustrated in Table 7: involuntary manslaughter (INV), belonging to the group of crimes against person; embezzlement (EMB), fraud (FRD), fraudulent insolvency (FRI), which are property crimes; bankruptcy (BKR), false seals (FLS), which belong to crimes against economy; crimes against the Public Administration (CPA). As shown in the second column of Table 7, the correlation coefficients vary between -0.48 (FRI) and -0.96

[10] The analysis has been performed using different threshold values of the explained variance; remarkably, the results do not change up to a threshold value of 65%, showing a good level of robustness.

(FRD). Furthermore, the ratios of the common component variance over the series variance are presented in the third column of Table 7; such common component explains a large part of the variance of CPA (85%), while the ratio reaches the lowest value in BKR (62%). Hence, this crime subset shows a strong relationship with the business cycle. As found in section 4.2, no violent crimes are 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; Fougre et al. 2007).

Figure 3 represents the graphics of the common components of the selected crime series and the business cycle. Notably, all crime variables, except for INV, exhibit a countercyclical behavior with respect to GDP (as indicated also in the fourth column of Table 7), which means that an increase of this type of criminal offenses is observed during recessions. This relationship is particularly evident after 1999, when GDP shows a clear growth until the end of 2000 and subsequently a long recession until June 2003. Furthermore, the cyclical signal of these types of crime is clearer than the one of the total crime, seen in Figure 2.

Looking at the finer details, we note that 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 7).

Bankruptcy, embezzlement, fraudulent insolvency, crimes against Public Administration 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. 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. Another possible interpretation is consistent with the idea that, at least in the recent history of recessions, global economic crises are preceded by financial crises; for example, NBER established that the beginning of the latest recession 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.

Following this strand of research, some specific crime fluctuations could lead to changes in GDP, contrary to what is generally observed in the crime economic literature. This interpretation would seem to indicate some form of cointegrated relationship, according to some intriguing analysis (for example, Hale, 1998 and 1999). Probably the most interesting interpretation is given by Field (1999), who finds the evidence of a long run cointegrating relationship between property crimes (theft and burglary) and other factors, such as consumption levels and number of young males, which implies a gradually changing equilibrium level of crime. We test the hypothesis of no cointegration between each selected crime typology and GDP series; by using the MacKinnon test, we cannot find any evidence of cointegration relationship.

The category of Crime against Public Administration, mostly made up of corruption offenses, reduces the efficiency of the production of public services and goods. Such negative effects can drive the whole economy down; as pointed out by Mauro (1995), using a cross section of countries, corruption reduces investment, thereby lowering economic growth.

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. We see that these crimes rise during recessions, and drop during expansions.

Before concluding the analysis of the typologies of crime, we want to underline some points. First,this latest selection seems partially in contrast with the analysis of the 6 groups. In particular, excluding CPA, which is also considered as a group per se in the previous analysis, the remaining variables belong to the crimes against economy (BKR and FLS), the property crimes (EMB, FRD and FRI), the crime against person (INV) groups. Being a small percentage of the corresponding grousp, their behavior with respect to the business cycle was obscured in the previous analysis despite the strong correlation. The results obtained are not less relevant: in spite of their low frequencies, the economic crimes have a greater social cost compared to the most frequent crimes, such as drug dealing and currency counterfeit (see Detotto and Vannini, 2010).

Secondly, our final selection is based on two factors, while the first analysis, shown in Table 6, was based on three factors. Hence, analyzing the contribution of each factor on the variance ratio in greater detail, we notice that the third factor seems strictly linked to the street crimes. In fact, REK, THF, DRG and OTC, the proportion of the variance explained by the third factor is greater than the proportion explained by the other factor and over 40%. Precisely, the first two typologies are the most frequent street crimes, whereas DRG is strictly related to street crimes; OTC contains a large set of crimes, including offenses like smuggling of weapons and cigarettes, correlated with the main street crimes.

Thirdly, we remark that our procedure of series selection is able to identify the crime variables most related to the business cycle; of course, this does not imply that the excluded variables have no relationship with the business cycle, but that, in the time span considered, they do not show a cyclical component strictly linked to the business cycle. For example, it could be possible that such a relationship is weaker in some subperiod and stronger in others. An alternative procedure is to extract a common component from groups of similar crimes and then compare it with the business cycle, as we will do in the next subsection.

Finally, we have checked if the frequency of data can affect the final output of the analysis: we have repeated the exercise using quarterly, seasonally adjusted and detrended data on GDP and crime. Now the matrix of data has dimension 56×23; probably the time dimension is too short for this type of technique. Anyway, the results seem sufficiently robust; in fact, the output confirms the previous findings, adding only two typologies, namely MUR (coincident) and SFR (lagged). But, interestingly, we have observed that, increasing the threshold for the variance ratio up to 70%, the monthly and quarterly analyses provide the same selected variables.

4.4 Street crimes and GDP

In the present subsection we analyze five crime typologies (ASS, MUR, SAS, REK and THF), generally included into street crime category (see, for example, Arvanites and Defina, 2006), which have been excluded from the final selection. The number of the selected factor is 2 and the share of the explained variance is very high for all variables (Table 8), varying from 60.5% for THF to 80.0% for MUR. The cycle behaviors are similar, except for ASS, which seems to be leading with respect to GDP.

Following Forni et al. (2001), it is possible to construct a coincident indicator of the street crimes, synthesizing the common components of each variable (apart ASS) in a single indicator. The indicator is simply a weighted sum of the components contained in χ^2: the weights are proportional to the average level of the corresponding crime variable across time. Of course, the highest weights are associated to THF and REK.

The coincident street crime indicator is plotted, with the GDP business cycle, in Figure 4. It can be noted that the coincident indicator resembles the behavior of the smoothed series of total crime, previously shown in Figure 1, even though it is more irregular. Notably, the correlation between business cycle and street crime cycle is equal to 0.06, justifying the exclusion of the street crimes from the selection made in the previous subsection. On the other hand, splitting again the sample in three sub-periods (1991-1995, 1996-2000, 2001-2004), we obtain correlations equal to 0.62, -0.63 and 0.29, respectively. In practice the findings indicate that the correlation between business cycle and street crimes is strong but changes along time, with a breakpoint in December 1995. In terms of Cantor and Land's (1985) theory, it seems that the opportunity effect prevails until 1995, which is a period characterized by a long recession; on the other side the motivation effect seems dominant from 1995 to 2000, when we have a frequent alternation of growth and recession periods of short duration.

As said in section 2, the street crimes constitute the 70% of total crimes, so the behavior of the coincident indicator is very similar to the dynamic of the TCR series, with a correlation of 0.69.

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.

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 initially in 6 groups and then in 22 crime types, and rerun the DFM. We find that seven crime types have a strong link with GDP. Most of the variables selected can be considered as white-collar crimes. Probably, the choice of GDP as variable representing the full economy, implies such result; maybe the use of other economic variables, more linked to social suffering, such as unemployment rate or income distribution index, could reveal a stronger relationship with street crimes. It is, however, a task for future researches.

An important novelty in this nonparametric approach is the detection of the cyclical component of the crime series and their classification as lagging, leading or coincident behavior with respect to GDP; we detect four series with a leading behavior, two lagging typologies 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 establish the cause-effect relationship between crime and economic fluctuations; our main result is that few crime offenses are strongly linked to the business cycle and that some of them are leading with respect to the business cycle.

Empirical analysis on crime cannot trascend problems due to undereporting and collection of data, which impose serious limits to the robustness of the results. In order to avoid such problems, we have selected a specific time span (1991-2004) in which no substantial law intervention and changes in police efficiency and in report propensity are observed.

As mentioned above, the purpose of our analysis is not to establish some causal relationship between crime and business cycle, but to verify if GDP and crime variables follow similar comovements. Anyway, this approach could be extended in order to answer questions in new empirical domains. For example, it could be a support for the identification of the number of lags with which the economy affects a certain type of crime. In such a case, we could include into the vector z_t in (3.1) other relevant variables, such as law enforcement, incapacitation, demographic variables, and verify the presence of some comovements with the observed crime variable. The existence of a relationship could encourage researchers to develop and implement valid parametric models to forecast changes in crime with significant policy implications.

Finally, in our analysis we observe that some crime typologies, namely bankruptcy, embezzlement and fraudulent insolvency, anticipate the business cycle. Further research could focus on this relationship between such illegal activities and financial economic variables in order to identify the channels through which they interact with each other. This issue deserves deeper analysis which we intend to address in the future.

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Tables

Table 1: Istat classification of crime typologies.

Crime group	Crime typology	Code
Crimes against person (CAP)	Assault	ASS
	Involuntary manslaughter	INV
	Murder	MUR
	Sexual assault	SAS
Crimes against family and decency (CFD)	Crime against the family	AGF
	Prostitution	PRS
Property crimes (PCR)	Property damage	DMG
	Embezzlement	EMB
	Fraud	FRD
	Fraudulent insolving	FRI
	Handling	HND
	Robbery, extortion and kidnapping	REK
	Theft	THF
Crimes against the economy (CAE)	Bankrupt	BKR
	Currency counterfeit	CCN
	Drug dealing	DRG
	Falsifying documents	FLD
	False seals	FLS
	Fraudulent trading	FRT
	Selling adultterared foodstuffs	SAF
Crimes against Public Administration		CPA
Other types of crimes		OTC

Table 2: Descriptive Statistics for the crime variables and GDP.

Series	% of TCR (*)	Min	Median	Max	Mean	RSD (**)	Normality Test (***)
GDP		85,090.47	94,061.78	103,289.01	94,115.03	0.06	5.61*
ASS	6.99%	6,943	17,170.5	25981	16,819.5	0.25	3.32
INV	0.24%	272	555.5	921	585.94	0.26	15.73***
MUR	0.11%	195	259.5	914	266.11	0.23	0.86
SAS	0.11%	95	289.5	525	269.42	0.41	0.38
AGF	0.30%	245	628.5	1808	723.52	0.39	26.17***
PRS	0.17%	204	364.5	766	403.65	0.29	50.22***
DMG	7.97%	8891	19,057.5	28,704	19,185.43	0.25	10.26***
EMB	0.26%	176	605	1172	622.61	0.31	24.59***
FRD	2.91%	1,825	5,056	42,513	7,003.31	0.79	3.03
FRI	0.17%	153	419	1137	406.09	0.29	0.63
HND	3.11%	2,702	7,889	16,119	7,480.71	0.31	1.58
REK	2.13%	3,339	4,679	5,135	5,113.93	0.14	0.48
THF	57.65%	95,862	135,414.5	185,305	138,705.3	0.13	12.03
BKR	0.16%	102	421	661	393.15	0.33	11.86***
CCN	1.28%	357	2,907	8,923	3,081.32	0.51	7.28**
DRG	2.46%	3,953	5,747.5	9,771	5,929.44	0.19	29.14***
FLD	3.54%	2,907	8,822	13,944	8,525.46	0.27	87.21***
FLS	0.23%	73	519.5	1,787	555.74	0.59	97.45***
FRT	0.04%	41	102	737	106.65	0.53	1.06
SAF	0.01%	2	11	180	13.03	1.07	8.85**
AGS	2.09%	2,269	5,289.5	8,994	5,039.27	0.21	1.42
OTC	3.27%	3,496	7,415.5	42,288	7,873.48	0.41	6.68**

Notes: (*) Average percentage of total crime; (**) Relative standard deviation, RSD, is the ratio of the standard deviation over the mean; (***) Normality test based on Kolmogorov-Smirnov statistic.

Table 3: Correlation between common parts of total crime series (for several lags and leads) and GDP. The bold number evidences the highest correlation.

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 4: Correlation between common parts of groups of crime series (for several lags and leads) and GDP. The bold numbers evidence the highest correlation.

	Lags												
	-6	-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5	+6
CAP	0.09	0.14	0.19	**0.21**	0.20	0.18	0.10	0.06	0.01	-0.04	-0.05	-0.03	0.02
CFD	-0.03	-0.07	-0.13	-0.24	-0.36	-0.48	**-0.62**	-0.58	-0.53	-0.44	-0.34	-0.22	-0.10
PCR	0.01	-0.15	-0.28	-0.40	-0.48	-0.54	**-0.56**	-0.37	-0.20	-0.06	0.03	0.08	0.09
CAE	-0.08	-0.14	-0.23	-0.34	-0.43	-0.52	**-0.61**	-0.55	-0.46	-0.36	-0.27	-0.18	-0.10
CPA	-0.10	-0.18	-0.28	-0.41	-0.56	-0.70	**-0.82**	-0.73	-0.63	-0.52	-0.39	-0.25	-0.14
OTC	-0.05	-0.12	-0.19	-0.26	-0.32	-0.41	**-0.49**	-0.34	-0.28	-0.22	-0.17	-0.12	-0.06

Table 5: Analysis of the common parts of crime groups series and GDP.

Series name	Ratio common component variance**	Phase classification	Series classification
CAP	0.61	(+)	Lagging
CFD	0.57	(-)	Leading
PCR	0.37	(-)	Lagging
CAE	0.74	(-)	Leading
CPA	0.77	(-)	Leading
OTC	0.68	(-)	Lagging

Notes:(*) 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 6: Analysis of the common parts of crime typologies series and GDP.

Crime Group	Series name	Common parts correlation* (lags)	Ratio common component variance**				Phase classification	Series classification
			total	%fac.1	%fac.2	%fac.3		
	GDP		0.64	39.1%	45.7%	15.2%		
CAP	ASS	0.19 (-1)	0.69	37.1%	42.3%	20.6%	(+)	Lagging
CAP	INV	0.58 (0)	0.61	20.1%	67.1%	12.9%	(+)	Coincident
CAP	MUR	0.32 (0)	0.56	26.0%	41.6%	32.4%	(+)	Coincident
CAP	SAS	0.14 (-2)	0.74	31.6%	44.8%	23.6%	(+)	Lagging
CFD	AGF	-0.24 (+2)	0.33	39.1%	45.7%	15.2%	(-)	Leading
CFD	PRS	-0.73 (0)	0.45	44.0%	34.2%	21.8%	(-)	Lagging
PCR	DMG	-0.40 (0)	0.56	84.6%	7.7%	7.7%	(-)	Lagging
PCR	EMB	-0.79 (0)	0.79	69.1%	25.6%	5.3%	(-)	Leading
PCR	FRD	-0.87 (0)	0.59	40.9%	23.5%	35.6%	(-)	Lagging
PCR	FRI	-0.56 (0)	0.70	86.7%	4.4%	8.9%	(-)	Lagging
PCR	HND	0.16 (-3)	0.40	48.5%	41.4%	10.1%	(+)	Lagging
PCR	REK	0.09 (-4)	0.56	6.1%	27.8%	66.1%	(+)	Lagging
PCR	THF	-0.21 (-1)	0.41	27.1%	16.2%	56.7%	(-)	Lagging
CAE	BKR	-0.67 (0)	0.60	88.6%	4.5%	6.9%	(-)	Leading
CAE	CCN	-0.06 (-4)	0.54	57.2%	34.7%	8.1%	(-)	Lagging
CAE	DRG	0.27 (-2)	0.50	22.4%	35.5%	42.1%	(+)	Lagging
CAE	FLD	0.07 (-3)	0.59	54.9%	37.9%	7.2%	(+)	Lagging
CAE	FLS	-0.60 (0)	0.71	87.9%	4.4%	7.8%	(-)	Lagging
CAE	SAF	-0.26 (-1)	0.48	28.3%	47.9%	23.8%	(-)	Lagging
CAE	SFR	-0.35 (0)	0.56	77.5%	12.0%	10.6%	(-)	Leading
CPA	CPA	-0.78 (0)	0.82	86.1%	10.5%	3.4%	(-)	Leading
OTC	OTC	-0.51 (0)	0.40	24.6%	21.4%	54.0%	(-)	Leading

Notes: (*) Highest cross-correlation between common parts of series (with lag indicated in parentheses) 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 7: Analysis of the common parts of crime typologies series and GDP.

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

Notes: (*) Highest cross-correlation between common parts of series (with lag indicated in parentheses) 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 8: Variance ratio of the common components of street crimes.

ASS	MUR	SAS	REK	THF
0.738	0.800	0.755	0.678	0.605

Figures

Figure 1: Linear detrended series of GDP (gray line, left scale) and (smoothed) total crime in Italy (black line, right scale).

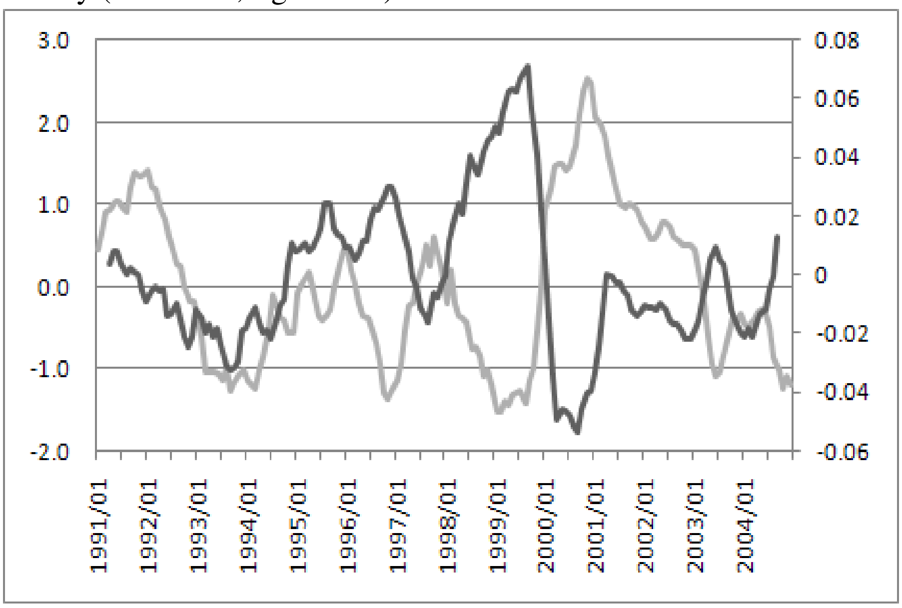


Figure 2: Cyclical components of GDP (gray line) and TCR (black line).

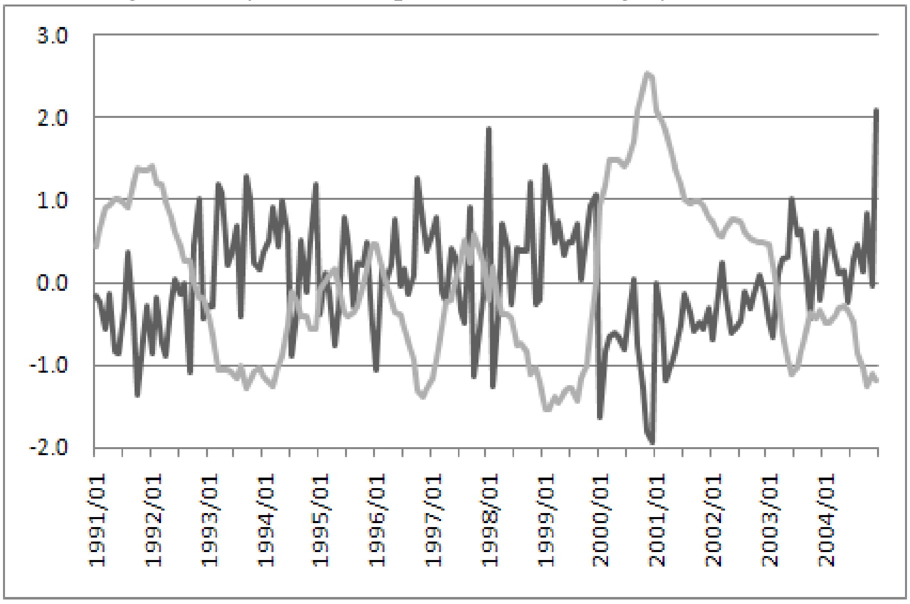


Figure 3: Cyclical components of GDP (gray line) and selected typologies of crime.

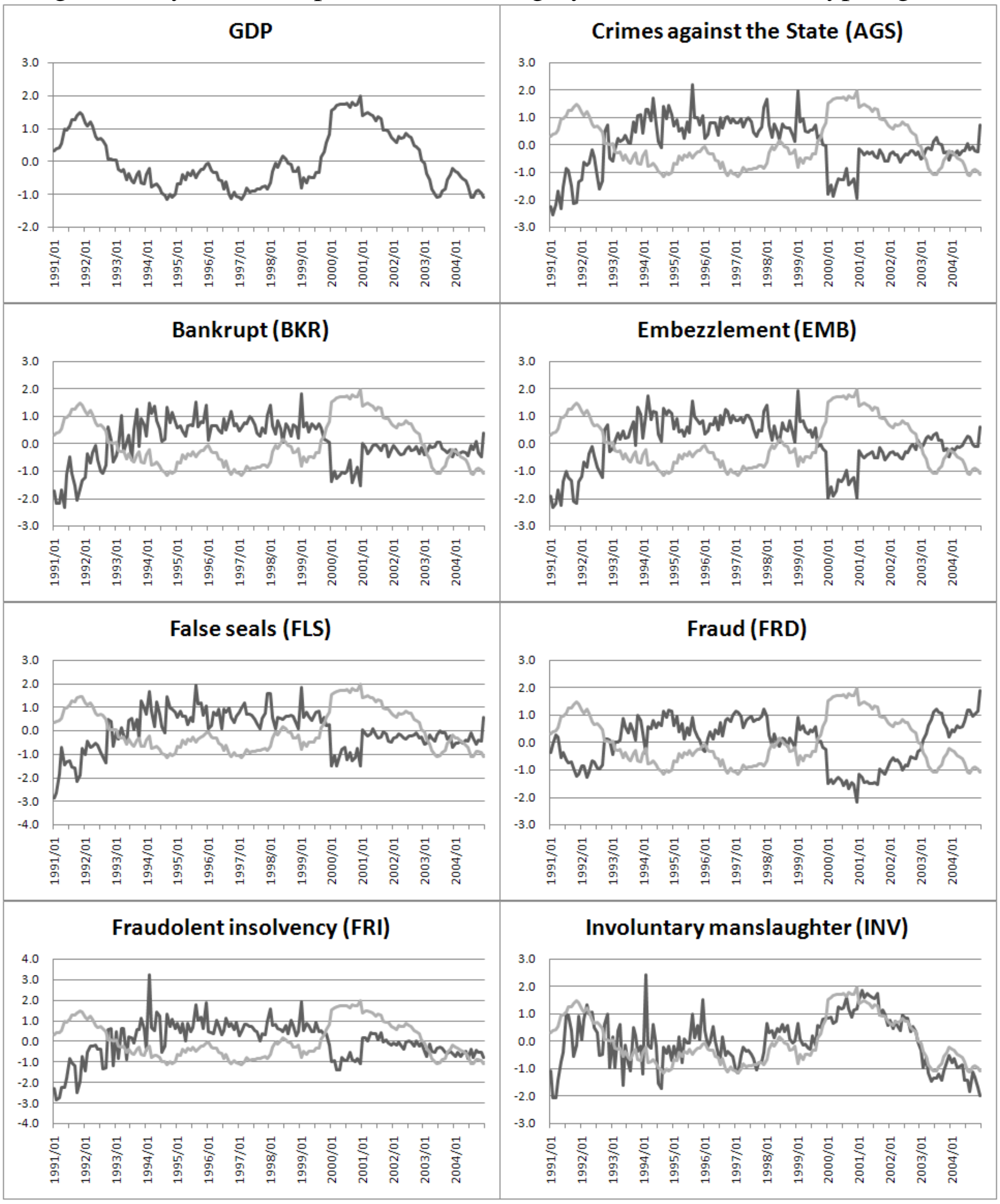
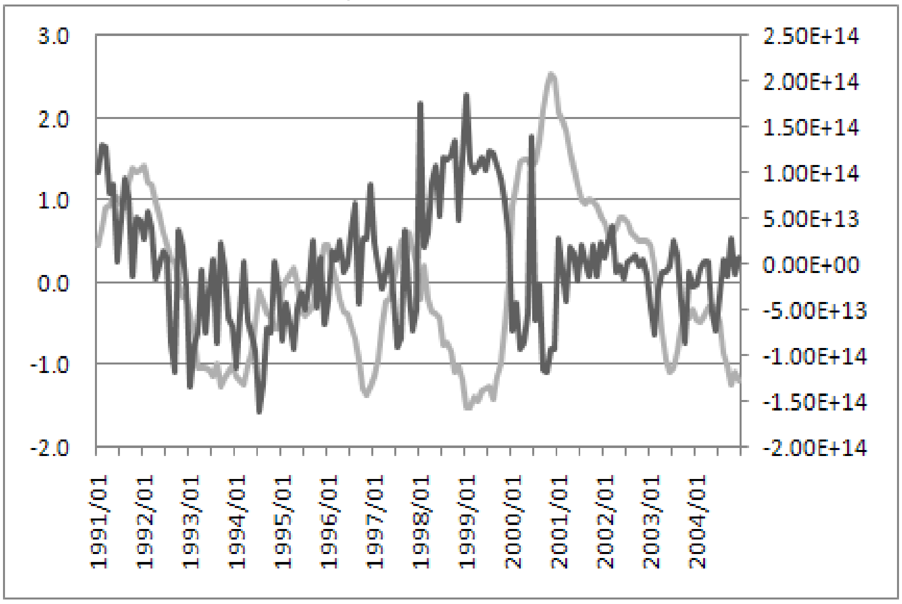


Figure 4: Cyclical components of GDP (gray line, left scale) and common component of street crimes (black line, right scale).



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