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Crime, deterrence, inequality, unemployment, panel cointegration, cross- section dependence

JEL Codes
C33, E20, K40

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Common trends in the US state-level crime. What do panel data say?

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Abstract

This paper aims to investigate the long-run relationship between crime, inequality, unemployment and deterrence using state-level data for the US over the period 1978-2013. The novelty of the paper is to use non-stationary panels with factor structures. The results show that: *i*) a simple crime model well fits the long run relationship; *ii*) income inequality and unemployment have a positive impact on crime, whereas deterrence displays a negative sign; *iii*) the effect of income inequality on crime is large in magnitude; *iv*) property crime is generally highly sensitive to deterrence measures based upon police activities.

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1 Introduction

The wide variation in crime rates over time and across regions has triggered a vast literature in criminology, sociology, and economics, with the aim to explain the determinants of crime. Since the seminal works of Becker (1968) and Ehrlich (1973), several studies have investigated how inequality, labor market conditions and deterrence activities may affect crime rates in the US. Examples of this literature are: Marvell and Moody (1994), Levitt (1996), Doyle et al. (1999), Becsi (1999), Kelly (2000), Raphael and Winter-Ebmer (2001), Gould et al. (2002), Levitt (2002), Vieraitis et al. (2007), Choe (2008), Lin (2009), Johnson and Raphael (2012), Chintrakarn and Herzer (2012), and Neal (2015).

In general, empirical results point to deterrence as a valid instrument to reduce crime. In particular, higher incarceration rates are associated with lower crime rates (Marvell and Moody, 1994; Levitt, 1996; Becsi, 1999; Doyle et al., 1999; Raphael and Winter-Ebmer, 2001; Vieraitis et al., 2007),[1] and more intense police activities are accompanied by a reduction in crime (Kelly, 2000; Levitt, 2002; Evans and Owens, 2007; Lin, 2009).[2] Only a few exceptions find a positive relationship between police and crime (see e.g. Becsi, 1999; Doyle et al., 1999).

As for the impact of unemployment rate and income inequality on crime, there is a general consensus that higher unemployment rates (Levitt, 1996; Doyle et al., 1999; Raphael and Winter-Ebmer, 2001; Gould et al., 2002) and income inequality (Kelly, 2000; Choe, 2008; Neal, 2015) increase crime.

The majority of above studies uses static panel regressions, with linear time trend (Raphael and Winter-Ebmer, 2001; Gould et al., 2002) and time fixed effects (Vieraitis et al., 2007; Evans and Owens, 2007; Johnson and Raphael, 2012) to take trends and cross-section dependence in the data into account. However, while the trend deterministic component ignores the long-run movement of data, the specific time fixed effects are likely to produce misleading inference unless the pair-wise cross-correlations are identical (see Blomquist and Westerlund, 2014).

Chintrakarn and Herzer (2012) use panel cointegration techniques to deal with trending behaviour in crime rates when estimating the long-run relationship between crime and inequality in the US. Their empirical results show that the top 10% income share and the Gini coefficient have a negative impact on crime rates. These results may reflect the fact that the estimator used in the analysis is derived under the unrealistic assumption of cross-section independence. In fact, Neal (2015) shows that, once cross-section dependence is taken into account, a positive relationship between crime and inequality is found.

This paper aims to estimate the long run relationship between different types of crime,

[1] Spelman (2006) concludes that a 10% increase in imprisonment rates produces on average a 2-4% decrease in crime rates.

[2] Nagin (2013) summarizes that "studies of police presence consistently find that putting more police officers on the street has a substantial deterrent effect on serious crime."

unemployment, inequality and deterrence activity in the US at state-level over the period 1978-2013 using techniques based on a common factor structure. To get a feeling for the presence of common factors among the two main type of crimes (property and violent crime) in the US, in Figure 1 we report the estimated first principal component of the growth rate of crime of the states grouped in the same region (Northeast, South, West, Midwest) along with the aggregate crime growth pattern.[3] It clearly emerges that the rates of crime across states tend to move together with the US aggregate crime growth rate. This suggests that the states under investigations are largely interconnected. Therefore, in this context, the use of an econometric methodology that accounts for cross-section dependence seems to be appropriate.

In our empirical analysis, we proceed in three steps. We first test for unit root in the data using the PANIC approach by Bai and Ng (2004), and then we check for cointegration using the Durbin-Hausman type panel co-integration by Westerlund (2008). Lastly, we estimate the crime equation, which we derive from the theoretical approach by Edmark (2005) and Wu and Wu (2012), using the continuously-updated (CUP) estimator developed by Bai and Kao (2006), that controls for serial correlation and endogeneity. We use several measures of crime rates (property, violent, robbery, burglary, larceny and auto theft), inequality (top 10% and top 5% of income earners, and Gini index), and two measures of crime prevention (prison admissions per crime and state expenditure in police defense).

This paper contributes to the empirical literature on crime in the US in some respects. First, to the best of our knowledge, this is the first paper to estimate the long-run relationship between crime, unemployment, inequality, and deterrence in the US using non-stationary panels. This represents a further step in the analysis for crime in the US, since previous studies have only focused on crime and inequality (see Chintrakarn and Herzer, 2012; Neal, 2015). Second, this paper uses factor models to deal with cross-section dependence (see Blomquist and Westerlund, 2014; Birkel, 2014). Third, we use a recently developed estimator for nonstationary panels that control for endogeneity and serial correlation. Lastly, we offer a sensitivity analysis for crime using different measures of crime, deterrence and inequality.

Our empirical analysis delivers four main results. First, our crime model well fits the long run relationship between different type of crimes, inequality, unemployment and deterrence measures, as strong evidence of co-integration is found. Second, the elasticities of crimes with respect to inequality and unemployment are generally positive, whereas those of deterrence measures display a negative sign. Third, all types of crime appear to be more sensitive to inequality measures that consider the share of total income within a larger population (i.e. top 10% instead of 5%). This result suggests that rich people, but not top income earners, are more likely to be targeted by criminal activities (see Allen, 1996; Demombynes and Özler, 2005). Fourth, police activities play a major role in reducing

[3] The regional categorization follows the US Bureau classification.

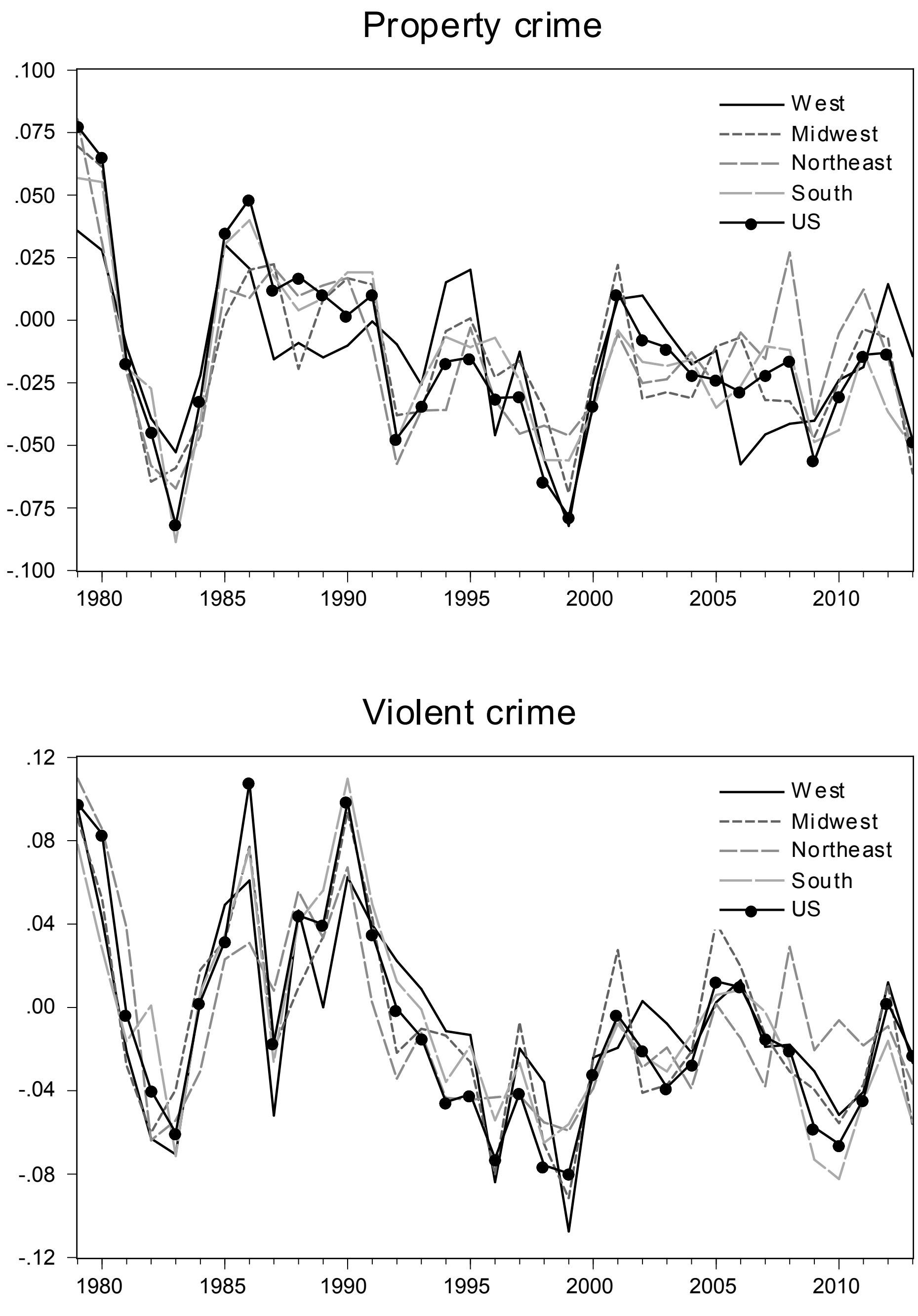

Figure 1: Estimated first principal component of the crime growth rates of various US states entering in the same regions (Northeast, South, West, Midwest) and aggregate crime growth pattern.

property crime than prison admissions, while the effect of the two measures of deterrence on violent crime is similar in magnitude (see also Devine et al., 1988; Levitt, 1996; Spelman, 2005).

The paper is organised as follows. Section 2 presents the theoretical model of crime that represents the basis of our empirical analysis. Section 3 describes the data and econometric methodology used. Section 4 discusses the empirical results. Section 5 draws conclusions.

2 Theoretical model

Our crime model is inspired by the principles in Becker (1968) and follows the formulation in Freeman (1999), Edmark (2005), and Wu and Wu (2012).[4] The model describes the choice of the individuals between work and crime, as their source of income during one period. This means that work and crime are regarded as substitutes and cannot be combined. Accordingly, we indicate with W the wage from honest work, whereas W_b is the income from illegal activities. Like Edmark (2005), the presence of a idiosyncratic psychological cost (c) of committing a crime is also considered. This cost, that can be positive or negative, is assumed to be independent and continuously distributed over the population. The rational choice of crime satisfies the following condition:

$$E\left(W_b\right) - c > E\left(W\right). \tag{1}$$

According to (1), an individual will commit a crime if the expected return from crime, minus the psychological cost, is higher than the expected return from honest work. Formally, the expected return from crime is as follows:

$$E\left(W_b\right) = \left(1 - p\right) W_b + p\left(W_b - S\right), \tag{2}$$

where p represents the probability of being caught for an individual engaged in criminal activities and S is the cost of punishment.[5] The latter comprises fines, time spend in jail, low standard of living in prisons, reduction in reputation, and restrictions on future employments, among others.

The expected income from honest work is defined as follows:

$$E\left(W\right) = \left(1 - u\right) W + uA, \tag{3}$$

where u indicates the unemployment rate, defined as the probability of being unemployed, and A is the unemployment benefit. Substituting Eq.s (3) and (2) into condition (1), one yields the following inequality:

[4] The model presented here is a static model as in Edmark (2005) and is sufficient to represent the argumentations of the empirical framework.

[5] For simplicity, but without loss of generality, we assume that, when a criminal is caught, he is promptly incarcerated. This implies that the probabilities of being caught and incarcerated coincide.

$$c < [(1-p)\,W_b + p\,(W_b - S)] - [(1-u)\,W + uA]\,. \tag{4}$$

The above formula states that an individual chooses to commit a crime instead of working honestly if the psychological cost of committing a crime (i.e. c) is lower than the quantity on the right-hand side. Moreover, it helps to elicit the effect of the parameters of the model on the supply of crime at more aggregate level (see Edmark, 2005). In fact, the higher is the right-hand side of (4), the higher is the probability for individuals to commit crimes, with an impact on the aggregate supply of crime.

The following three hypothesis are used to further specify the right-hand side of (4):

Hypothesis 1 *(Edmark, 2005): Assume that $W > A$ and $u < 1$ (both realistic assumptions). This implies that the right-hand side of Eq. (4) is increasing in u, because the quantity $[(1-u)\,W + uA]$ goes down as u rises.*

Hypothesis 2 *(Freeman, 1999): Assume that individuals who are likely to commit crimes are low skilled workers. W is likely to be far lower than the average wage of population.*

Hypothesis 3 *(Freeman, 1999): Assume that W_b depends proportionally to the income of the higher paid (H): $W_b = vH$, with $v < 1$, and the cost of punishment (S) is proportional on the legal earnings of the criminal: $S = qW$, with $q < 1$.*

As a result, the right-hand side of Eq. (4) can be written as:

$$[(1-p)\,vH + p\,(vH - qW)] - [(1-u)\,W + uA]\,. \tag{5}$$

Relation (5) is increasing in earning inequality, which is defined as $W_{sp} = H - W$. This implies that the greater the income inequality, the greater the incentive to commit crimes. Relation (5) increases even when income of low and high paid workers rises of the same percentage.[6]

In a nutshell, condition (5) is an increasing function in u and W_{sp}, and a decreasing function in c, p and A. The above key variables allows us to introduce the supply function of crime (C^s):

$$C^s\left(\overset{+}{W}_{sp}, \overset{-}{p}, \overset{-}{A}, \overset{+}{u}, \overset{-}{c}\right). \tag{6}$$

[6]A numerical example may clarify this point. Suppose that u=0.08, W=2 and A=1.5. For simplicity assume that $p = q = v = 0.5$. The condition for having a positive value of (5) is that $\frac{H}{W} > \frac{1}{v}[pq + (1-u) + u\frac{A}{W}]$. In this case, it suffices that $\frac{H}{W} > 2.46$. Since $W = 2 \Rightarrow H > 4.92$. Fixing $H = 6$, we have that the condition (5) is equal to 0.54. Now, let assume that both H and W rise by 10%, then $H - W$ will rise (i.e. from 4 to 4.4). The net effect on (5) is positive: the quantity now is equal to 0.6.

In order to derive the effects that variables in (6) have on crime in a general equilibrium setting, we also need to consider the demand function, which comes from potentially black market buyers searching for illicit products (a typical example is the demand for illicit drugs). Higher income levels are generally associated with a larger demand for crime (Edmark, 2005). This effect works in the opposite direction compared to that related to the supply function. The aggregate demand of crime (C^d) can be then written as:

$$C^d\left(\overset{+}{W}\right). \tag{7}$$

Relation (7) has implications for the effects of income on crime. For a given H, a rise in W (and therefore a decrease in income inequality) produces a positive effect on demand, but a negative one on supply. Again, an ambiguous final effect on crime is observed through an increase in unemployment. In fact, higher levels of unemployment may negatively affect aggregate income and, if the impact on W is higher than that of H,[7] then there will be an increase in the supply and decrease in the demand. Putting together relations (6) and (7), we have the following:

$$C^*\left(\overset{?}{W}_{sp}, \overset{-}{p}, \overset{-}{A}, \overset{?}{u}, \overset{-}{c}\right), \tag{8}$$

where (C^*) represents the quantity of crime that equates demand and supply. The question mark above income inequality and unemployment rate indicates that it is not possible to define *a priori* the sign of these variables.

Violent crimes (aggregate violent and robbery crimes) are also considered in this work, even though our theoretical rationale is not strictly related to these kind of crimes. This is because, as argued by Grogger (2006), theoretical frameworks of property crime can be used to explain economically motivated offences that are committed through the use of violence. Further, Kelly (2000) and Edmark (2005) argue that unemployment and income inequality may affect violent crimes.[8]

3 Data and econometric specification

Our primary goal is to estimate a crime model that reflects as much as possible the theoretical framework described in Section 2. More specifically, we estimate the following log-log model using annual data over the period 1978-2013 (see Becsi, 1999; Edmark, 2005; Vieraitis et al., 2007; Choe, 2008; Lin, 2009):[9]

[7]It is plausible to assume that an unemployment shock (for example due to a technology innovation) will have a big impact on low skilled workers (see e.g. Brynjolfsson and McAfee, 2014).

[8]In the strain theory of Merton (1938), it is stressed that individuals in low scale of social structure tend to feel disadvantaged and alienated and, in response to that, they are more inclined to commit violent crime.

[9]The main advantage of this the model is that the related estimates of the parameters represent the elasticity of the explanatory variables respect to crime rate.

$$ln\left(\frac{O}{N}\right)_{it} = \alpha_i + \beta_1 lnW_{sp,it} + \beta_2 lnu_{it} + \beta_3 lnp_{it} + \varepsilon_{it}, \tag{9}$$

where $\frac{O}{N}$ is the crime rate, that is the number of crimes (O) in each US state divided per 100,000 population (N), $W_{sp,it}$ is income inequality, u_{it} is the unemployment rate, and p_{it} indicates the risk of getting caught.[10] We use six categories of crimes, namely property, robbery, burglary, larceny theft, auto theft, and violent. Income inequality is measured as share of personal income received by the richest 10% state population (see Frank, 2009; Chintrakarn and Herzer, 2012). The probability of being caught is not directly observable, and is usually captured by deterrence measures (see also Witt et al., 1998; Edmark, 2005; Wu and Wu, 2012). In this paper, we use prison admissions per crime (*prison*) and state expenditure in police defence in percentage of the total state spending (*police*).[11] In addition, for a robustness check, we also estimate Eq. (9) using two additional income inequality measures: top 5% and Gini index (see also Bourguignon et al., 2003; Chintrakarn and Herzer, 2012). For details on data source, see Data Appendix.

Our analysis uses techniques based on a common factor structure. We proceed in three steps. Notably, we first test for unit root in all the variables of interest using the PANIC approach by Bai and Ng (2004), and then test for cointegration using the approach by Westerlund (2008). Lastly, we estimate the parameters in eq. (9) using the CUP estimator proposed by Bai and Kao (2006).

The Bai and Ng (2004) approach tests for the presence of a unit root in the common factors and idiosyncratic components separately. Bai and Ng (2004) consider the following factor model:

$$Y_{it} = c_i + \lambda_i' F_t + e_{it}, \tag{10}$$

where c_i is a polynomial trend function, F_t is an $r \times 1$ vector of common factors, λ_i is the corresponding vector of factor loadings, and e_{it} denotes the idiosyncratic error.[12] Model (10) can be expressed in first difference as follows:

$$x_{it} = \lambda_i' f_t + z_{it}, \tag{11}$$

where $x_{it} = \Delta X_{it}$, $f_t = \Delta F_t$ and $z_{it} = \Delta e_{it}$. Bai and Ng (2004) apply the principal component analysis to x to obtain $\mathbf{r}$ estimated factors f_t, the corresponding factor loadings λ_i', and the estimated residuals $\hat{z}_{it} = x_{it} - \hat{\lambda}_i' \hat{f}_t$. For $t = 2, ..., T$, Bai and Ng (2004) define:

[10] The average of unemployment benefits (A) and the psychological cost of crime (c) are not included in specification (9) due to the lack of data (see also Edmark, 2005).

[11] Both measures of deterrence may suffer from simultaneity bias in crime equations. Here, we address this issue by using the CUP estimator that accounts for endogeneity. In addition, prison admission may suffer from *ratio bias* (see Fisher and Nagin, 1978) especially when crime equations are estimated in first difference. In general, there is very little evidence of *ratio bias* for the US data (see Levitt, 1998).

[12] See Bai and Ng (2004) for the model with constant and trend.

$$\hat{e}_{it} = \sum_{s=2}^{t} z_{it},\ i = 1, ..., N,$$
$$\hat{F}_t = \sum_{s=2}^{t} \hat{f}_s,\ \text{an}\ \ r \times 1\ \ \text{factor}.$$

The process Y_{it} in (10) may be nonstationary if one or more of the common factors are nonstationary, and/or the idiosyncratic error is nonstationary. To test for the unit root in the common factor components, Bai and Ng (2004) distinguish two different cases depending on the number of common factors selected in the data. The procedure is straightforward when one common factor is extracted from the data (the ADF unit root test is applied to the estimated factor), while it is more complex when more than one factor is selected.[13]

To test the stationarity of the idiosyncratic component, Bai and Ng (2004) propose to pool the individual ADF t-statistics estimated components $\hat{e}_{it}$:

$$\Delta e_{it} = \delta_{i,0}\hat{e}_{i,t-1} + \sum_{j=1}^{p} \delta_{i,j}\Delta\hat{e}_{i,t-j} + \mu_{i,t}. \tag{12}$$

Let $ADF_{\hat{e}}^{c}(i)$ be the ADF t-statistic for the i-th country. The asymptotic distribution of the $ADF_{\hat{e}}^{c}(i)$ coincides with the Dickey-Fuller distribution for the case of no constant. However, these individual time series tests have the same low power as those based on the initial series. Bai and Ng (2004) proposed pooled tests based on Fisher's type statistics defined as in Choi (2001) and Maddala and Wu (1999). Let $P_{\hat{e}}^{c}(i)$ be the p-value of the $ADF_{\hat{e}}^{c}(i)$, then

$$Z_{\hat{e}}^{c} = \frac{-2\sum_{i=1}^{N}\log P_{\hat{e}}^{c}(i) - 2N}{\sqrt{4N}} \longrightarrow N(0,1) \tag{13}$$

After testing for unit root in the data, the analysis proceeds to check for cointegration among the variables in equation (9). To this end, we consider the Durbin-Hausman panel cointegration test proposed by Westerlund (2008). Consider the following model

$$y_{it} = \alpha_i + \beta x_{it} + z_{it}, \tag{14}$$
$$x_{it} = x_{it-1} + w_{it}. \tag{15}$$

The error term z_{it} is defined by the following equations

$$z_{it} = \lambda_i' F_t + e_{it}, \tag{16}$$
$$F_{jt} = \rho_i F_{jt-1} + \mu_{it}, \tag{17}$$
$$e_{it} = \phi_i e_{it-1} + \upsilon_{it}, \tag{18}$$

[13]For details, see Bai and Ng (2004).

where F_t is a k-dimensional vector of common factors F_{jt} with $j = 1, ..., k$ and λ_i is a vector of factor loadings. In equation (17), it is assumed that $\rho_j < 1$ for all j, so as to ensure that F_t is stationary. Therefore, the relationship in (14) is cointegrated if $\rho_i < 1$ and it is spurious if $\rho_i = 1$. In order to construct the test, Westerlund (2008) uses the approach developed by Bai and Ng (2004).[14] A test of the null hypothesis of no cointegration can be constructed as a unit root test of the recumulated sum of the defactored and first differentiated residuals. By taking firsts difference of (16), we have:

$$\Delta z_{it} = \lambda_i' \Delta F_t + e_{it}.$$

Since Δz_{it} is unknown, the method of the principal components is applied to its OLS estimate, which are:

$$\Delta \hat{z}_{it} = \Delta y_{it} - \hat{\beta}_i \Delta x_{it},$$

where $\hat{\beta}_i$ is obtaining by regressing Δy_{it} on Δx_{it}. Let λ, ΔF and $\Delta \hat{z}$ be $K \times N$, $(T-1) \times N$ matrices of stacked observations on λ_i, ΔF_t and $\Delta \hat{z}_{it}$, respectively. The principal components estimator $\Delta \hat{F}$ of ΔF can be gained by computing $\sqrt{T-1}$ times the eigenvectors corresponding to the K largest eigenvalues of the $(T-1) \times (T-1)$ matrix $\Delta \hat{z} \Delta \hat{z}'$, and the matrix of the factor loadings is given by $\hat{\lambda} = \Delta \hat{F}' \Delta \hat{z} / T - 1$. Once $\hat{\lambda}_i$ and $\Delta \hat{F}_t$ are obtained, the defactored and first differentiated residuals are given by

$$\Delta \hat{e}_{it} = \Delta \hat{z}_{it} - \hat{\lambda}_i' \Delta F_t, \tag{19}$$

that, recumulated, becomes:

$$\hat{e}_{it} = \sum_{j=2}^{t} \Delta e_{ij}. \tag{20}$$

Westerlund (2008) shows that $\hat{e}_{it}$ is a consistent estimates of e_{it}, and this ensures that a cointegration test can be implemented using (18) with $\hat{e}_{it}$ in place of e_{it}. Therefore, the null hypothesis of no cointegration is equivalent to testing whether $\phi_i = 1$ in the following regressions:

$$\hat{e}_{it} = \phi_i \hat{e}_{it-1} + error. \tag{21}$$

Westerlund (2008) develops two panel cointegration tests that are derived by applying the Durbin-Hausman principle to (21). As for the first test, called panel test, the null and the alternative hypothesis can be formulated as $H_0 : \phi_i = 1$ for all $i = 1, ..., n$ against $H_1^p : \phi_i = \phi_i$ and $\phi < 1$ for all i, the alternative hypothesis for the second test, named group mean test, is $H_1^p : \phi_i < 1$ for at least some i. In this paper, we apply the panel test as under the alternative hypothesis a common cointegrating relationship is shared by all

[14] As for the assumptions in the data generating process (17)-(18), see Westerlund (2008).

the units, and the long-run relationship (see equation 9) can be then estimated using the CUP estimator. The Durbin-Hausman panel test statistics is as follows:

$$DH_p = \hat{S}_n(\tilde{\phi} - \hat{y})^2 \sum_{i=1}^{n} \sum_{t=2}^{T} \hat{e}_{it-1}^2,$$

where $\hat{S}_n = \hat{\omega}_n^2/(\hat{\sigma}_n^2)^2$ indicates the variance ratio, with $\hat{\omega}_i = \frac{1}{T-1} \sum_{j=M_i}^{M_i} \left(1 - \frac{j}{M_i+1}\right) \sum_{t=j+1}^{T} \hat{\upsilon}_{it}\hat{\upsilon}_{it-j}$ being the consistent estimate of ω_i^2, the long variance of υ_{it}, which are the residuals from the OLS regression in (21), and M_i is a bandwidth parameter that determines how many autocovariances of υ_{it}.

Once evidence of a cointegrating relationship is found, the parameters in equation (9) are estimated by using the FM-CUP estimator proposed by Bai and Kao (2006):

$$\hat{\beta}_{CUP} = \left[\sum_{i=1}^{n} \left(\sum_{i=1}^{T} \hat{y}_{i,t}^{+}(\hat{\beta}_{CUP})(x_{i,t} - \tilde{x}_i)' - T\big(\hat{\lambda}'_i(\hat{\beta}_{CUP})\hat{\Delta}_{F\varepsilon i}^{+}(\hat{\beta}_{CUP}) + \hat{\Delta}_{\mu\varepsilon i}^{+}(\hat{\beta}_{CUP})\big) \right) \right] \left[\sum_{i=1}^{n} \sum_{t=1}^{T} (x_{i,t} - \bar{x}_i)(x_{i,t} - \bar{x}_i)' \right]^{-1}, \tag{22}$$

where $\hat{y}_{i,t}^{+} = y_{i,t} - \left(\hat{\lambda}_i'\hat{\Omega}_{F\varepsilon i} + \hat{\Omega}_{\mu\varepsilon i}\right)\hat{\Omega}_{\varepsilon i}^{-1}\Delta x_{i,t}$ indicates the transformation of the original dependent variable in order to correct for endogeneity, and $\hat{\lambda}_i'$ the estimated factor loadings.[15] The CUP-FM is constructed by estimating parameters, long-run covariances matrix (Ω) and factor loadings recursively. Thus $\hat{\beta}_{\mathrm{FM}}$, $\hat{\Omega}$ and $\hat{\Lambda}_i$ are estimated repeatedly, until convergence is reached.

4 Empirical Results

In order to detect cross-correlations in the data, we compute the pair-wise cross-county correlation coefficients of each variable along with the cross-sectional dependence (CD) test by Pesaran et al. (2008). The related results, reported in Table 1, show strong evidence of cross-correlation for all the examined variables.

In applying the Bai and Ng procedure to test for unit root described in previous section, we consider the common factors and the idiosyncratic components separately. As a preliminary step, the BIC 3 criterion developed by Bai and Ng (2002) is applied in order to select the number of common factors. The related results point to one common factor for each of the examined variables. The unit root results in Table 2 show that all the variables of interest are nonstationary processes.

[15] As for the use of the CUP estimator, see also Costantini and Gutierrez (2013).

Table 1: CD test results, 1978-2013.

Variables	Levels			First difference		
	$\hat{\bar{\rho}}$	CD	$\mathrm{p-value}$	$\hat{\bar{\rho}}$	CD	$\mathrm{p-value}$
Property	0.710	149.11	0.000	0.402	83.25	0.000
Robbery	0.351	73.75	0.000	0.258	53.48	0.000
Burglary	0.823	172.75	0.000	0.350	72.57	0.000
Auto theft	0.517	108.65	0.000	0.309	64.07	0.000
Larceny theft	0.625	131.17	0.000	0.381	78.94	0.000
Violent	0.313	65.76	0.000	0.283	58.64	0.000
Unemployment	0.676	141.89	0.000	0.697	144.24	0.000
Top10	0.871	182.82	0.000	0.445	92.23	0.000
Top5	0.913	191.81	0.000	0.598	123.86	0.000
Gini	0.886	186.03	0.000	0.553	114.56	0.000
Police	0.340	71.42	0.000	0.477	98.74	0.000
Prison (property)	0.949	199.37	0.000	0.277	57.35	0.000
Prison (robbery)	0.851	178.63	0.000	0.226	46.78	0.000
Prison (burglary)	0.957	200.94	0.000	0.327	67.65	0.000
Prison (auto theft)	0.845	177.42	0.000	0.221	45.79	0.000
Prison (larceny theft)	0.944	198.21	0.000	0.244	50.62	0.000
Prison (Violent)	0.865	181.74	0.000	0.226	46.74	0.000

Notes: Variables are expressed in log. Prison deterrence measure is expressed as inmates prison admission per crime (indicated in parenthesis). The average cross-correlation coefficient $\hat{\bar{\rho}} = (2/N(N-1))\sum_{i=1}^{N-1}\sum j = i + 1^N \hat{\rho_{ij}}$ is the average of the country-by-country cross-correlation coefficients $\hat{\rho_{ij}}$. CD indicates the Pesaran et al. (2008) test that is defined as $\sqrt{2T/N(N-1)}\hat{\rho_{ij}}$.

Table 2: Panel unit root test results, 1978-2013.

Variables	$BN_{ADF^c_{\hat{F}}}$	$BN_{Z^c_{\hat{e}}}$
Property	1.512 (1.000)	−0.593 (0.553)
Robbery	0.074 (0.960)	1.163 (0.245)
Burglary	−0.340 (0.907)	0.305 (0.761)
Auto theft	−0.021 (0.950)	−0.016 (0.987)
Larceny theft	1.039 (0.995)	−0.593 (0.553)
Violent	−1.345 (0.597)	−1.867 (0.062)
Unemployment	−1.585 (0.480)	3.664 (0.000)
Top10	−1.752 (0.398)	3.538 (0.000)
Top5	−2.157 (0.225)	6.441 (0.000)
Gini	−2.088 (0.250)	4.176 (0.000)
Police	−1.846 (0.353)	1.725 (0.084)
Prison (property)	−1.975 (0.295)	0.187 (0.852)
Prison (robbery)	−1.618 (0.463)	2.022 (0.043)
Prison (burglary)	−1.994 (0.288)	0.340 (0.955)
Prison (auto theft)	0.721 (0.990)	1.331 (0.183)
Prison (larceny theft)	−1.815 (0.368)	0.002 (0.998)
Prison (Violent)	−0.847 (0.792)	2.641 (0.008)

Notes: Variables are expressed in log. Prison deterrence measure is expressed as inmates prison admission per crime (indicated in parenthesis). The number of common factors (r) selected using the BIC 3 criterion is equal to 1. The maximum number of factors is set to 4. $BN_{ADF^c_{\hat{F}}}$ and $BN_{P^c_{\hat{e}}}$ denote the unit root tests by Bai and Ng (2004) on common factors and idiosyncratic components, respectively. The ADF test regression includes a constant. p-values are in parenthesis.

After checking for non-stationarity in the data, we test for panel cointegration among the variables in Eq. (9). More specifically, Table 3 reports the panel cointegration results when top 10% inequality measure is used, while Table 4 illustrates the results in case of top 5% and Gini inequality measures. Findings in Table 3 show that our model well fits the long-run relationship between the different types of crime, top 10% and deterrence measures, on the ground that strong evidence of cointegration is found. This result is also confirmed when top 5% and Gini measures are considered for a robustness check; only in one case there is no evidence of cointegration (i.e. top 5%, unemployment and prison admissions).

In Tables 5-7, the estimation results are reported. They are generally in line with the theoretical arguments provided in Section 2 and previous studies (see Section 1). In

Table 3: Panel cointegration results, 1978-2013. Measure of inequality: Top 10%.

	Equation 9 ($top10$, $unem.$, $police$)	Equation 9 ($top10$, $unem.$, $prison$)
Dependent variables	DH_p test (p−value)	DH_p test (p−value)
Property	4.700*** (0.000)	6.306*** (0.000)
Robbery	3.638*** (0.000)	1.502* (0.067)
Burglary	2.238** (0.013)	5.203*** (0.000)
Auto theft	2.210** (0.014)	1.653** (0.049)
Larceny theft	4.859*** (0.000)	7.506*** (0.000)
Violent	7.055*** (0.000)	2.003** (0.023)

Notes: Variables are expressed in log (see Eq. (9)). Prison deterrence measure is expressed as inmates prison admission per crime. *,**, and *** indicate significance at 10%, 5%, and 1% level. p-values are reported in parenthesis.

particular, the supply effects of crime seem to prevail on demand effects, since crime elasticities with respect to inequality measures and unemployment are mostly positive. Similar results are found in Levitt (1996), Becsi (1999), Raphael and Winter-Ebmer (2001), and Neal (2015). It should be noted that, on average, the estimated elasticities of both property and violent crime with respect to unemployment are close in magnitude to those found in Levitt (1996), whereas the elasticity with respect to *prison* is within the range suggested by Spelman (2006). In addition, while the effect of *police* on property crimes turn to be similar to that in Lin (2009), it differs slightly from that in Lin (2009) in case of violent crimes.

Table 4: Panel cointegration results, 1978-2013. Measure of inequality: Top 5% and Gini.

	Equation 9 ($top5$, $unem.$, $police$)	Equation 9 ($top5$, $unem.$, $prison$)	Equation 9 ($Gini$, $unem.$, $police$)	Equation 9 ($Gini$, $unem.$, $prison$)
Dependent variables	DH_p test (p−value)	DH_p test (p−value)	DH_p test (p−value)	DH_p test (p−value)
Property	3.421*** (0.000)	6.714*** (0.000)	5.566*** (0.000)	5.473*** (0.000)
Robbery	3.473*** (0.000)	1.472* (0.070)	4.229*** (0.000)	1.709** (0.044)
Burglary	2.612*** (0.004)	4.473*** (0.000)	6.010*** (0.000)	6.980*** (0.000)
Auto theft	2.073** (0.019)	−0.157 (0.438)	4.017*** (0.000)	1.321* (0.093)
Larceny theft	3.442*** (0.000)	7.813*** (0.000)	5.323*** (0.000)	10.124*** (0.000)
Violent	4.193*** (0.001)	3.012*** (0.001)	4.719*** (0.000)	3.455*** (0.000)

Notes: Variables are expressed in log (see Eq. (9)). Prison deterrence measure is expressed as inmates prison admission per crime *,**, and *** indicate significance at 10%, 5%, and 1% level. p-values are reported in parenthesis.

As regards the effect of income inequality on crime, it is evident from Tables 5-7 that, on average, the elasticities of property crime with respect to all inequality measures are larger than those of violent crimes. This pattern is also highlighted in Levitt (1996) and Raphael and Winter-Ebmer (2001). This is because property crimes are primarily committed for economic reasons. It is also important to note that the elasticities for different type of crimes with respect to both top 10% and Gini index measures are larger than those related to top 5%. These results are in line with arguments developed in Allen (1996) and Demombynes and Özler (2005). In particular, Allen (1996) states that "in response to crime fears arising from inequality, upper-income crime targets have undertaken self-protective measures that may have offset criminal opportunities created by income inequality." Therefore, this is not true for lower income earners.

The findings concerning deterrence measures show that property crime is generally more sensitive to *police* than *prison*, while this difference disappears in case of violent crimes. This may be due to the fact that the threat of incarceration, captured by *prison*, is rather weak for property crimes, since in general the latter does not involve tough sanctions. This argument may also be used to explain differences among auto theft and the aggregate level of property crime in terms of sensitivity to *police* (see Tables 5-7). In fact, auto theft involves both criminal and illegal activities of stealing and selling cars, which are generally sanctioned as violent crimes (see Rosenmerkel et al., 2009; Longman, 2006).

With regard to the impact that labour market conditions have on the two main forms of crimes, the results show that property crimes are on average more sensitive to unemployment than violent crimes (see also Levitt, 1996; Donohue and Levitt, 2001; Raphael and Winter-Ebmer, 2001).[16]

Our analysis highlights that income inequality plays a crucial role in affecting all types of crimes. Therefore, reducing this condition should be a target in order to combat crime. Inequality not only poses moral questions, but also impact on the economic growth trough an increase in crime. In fact, higher crime rates are likely to reduce the return to legal activities, and may provide further incentives for individuals to seek illegal income, with an adverse effect on investments and human capital accumulation (see Josten, 2003). Therefore, redistributive policies that tend to sustain personal income of more disadvantaged individuals may be recommend to this end, especially when unemployment is high, with a particular beneficial impact on property crime.

Turning to the role of deterrence on crime, police enforcement activities seem to exert a different effect on the two main types of crimes: a rise by 1% of *police* causes on average a reduction in property and violent crime by 0.98% and 0.25%, respectively. This implies that, in those states where violent crimes are significantly high, a rise in police forces may not produce the expected result in terms of offenses reduction. In addition, any reinforce-

[16] It should be noted that auto theft crime regression shows no cointegration for top 5%, unemployment and *prison*, while it is instead statistically significant with top 10%, unemployment and Gini measures (see Table 4.).

ment of imprisonment policy may be not particularly convenient for a state government. This is because the effect of *prison* on property crime is much weaker than that of *police* (the average estimated elasticity of property crime with respect to *prison* is rather small and equal to 0.14%) and the effect on violent crime is only slightly larger than that of *police* (the average estimated elasticity of violent crime with respect to *prison* is 0.37%). As a result, pursuing tough imprisonment policies may not lead to significant gains in terms of reduction in crime, and states may face unsustainable costs with no benefit for the society (see Henrichson and Delaney, 2012; Kearney et al., 2014).[17]

Table 5: Estimation results of Equation (9), 1978-2013. Measure of inequality: Top 10%.

Variables	property	burglary	auto theft	larceny theft	violent	robbery
Top10	2.985***	1.428***	1.711***	3.032***	2.655***	1.269***
	(0.244)	(0.210)	(0.213)	(0.232)	(0.194)	(0.160)
Unemployment	0.618***	0.721***	−0.038	0.550***	0.271***	0.217***
	(0.048)	(0.041)	(0.042)	(0.046)	(0.038)	(0.032)
Police	−1.039***	−0.864***	−0.621***	−1.030***	−0.324***	−0.680***
	(0.136)	(0.117)	(0.116)	(0.129)	(0.109)	(0.092)
Variables	property	burglary	auto theft	larceny theft	violent	robbery
Top10	3.547***	1.711***	4.375***	3.919***	3.977***	2.943***
	(0.261)	(0.225)	(0.211)	(0.246)	(0.195)	(0.162)
Unemployment	0.697***	0.797***	0.114***	0.626***	0.281***	0.201***
	(0.048)	(0.042)	(0.040)	(0.045)	(0.037)	(0.031)
Prison	−0.104*	−0.031	−0.545***	−0.181***	−0.335***	−0.361***
	(0.064)	(0.049)	(0.041)	(0.062)	(0.047)	(0.033)

Notes: Variables are expressed in log (see Eq. (9)). Prison deterrence measure is expressed as inmates prison admission per crime. Standard errors are in parenthesis. *,** ,*** indicate significance at 10%, 5% and 1% level.

[17] A reinforcement of imprisonment policies may also produce a rise in wage inequality with an increasing impact on crime (Western et al., 2001; Western and Pettit, 2002). Individuals that are released from prison may suffer from low earnings and irregular employment. This may cause deterioration in job skills, and undermine potential connection with job opportunities. All this may produce an increase in crime (see Hagan, 1993).

Table 6: Estimation results of Equation (9), 1978-2013. Measure of inequality: Top 5%.

Variables	property	burglary	auto theft	larceny theft	violent	robbery
Top5	2.132^{***} (0.183)	0.974^{***} (0.156)	1.203^{***} (0.158)	2.183^{***} (0.174)	1.918^{***} (0.145)	0.912^{***} (0.121)
Unemployment	0.753^{***} (0.050)	0.778^{***} (0.043)	0.040 (0.044)	0.692^{***} (0.048)	0.395^{***} (0.040)	0.282^{***} (0.034)
Police	-1.111^{***} (0.134)	-0.904^{***} (0.115)	-0.649^{***} (0.115)	-1.098^{***} (0.128)	-0.381^{***} (0.108)	-0.702^{***} (0.091)
Variables	property	burglary	auto theft	larceny theft	violent	robbery
Top5	2.258^{***} (0.196)	0.819^{***} (0.171)	-	2.613^{***} (0.185)	2.856^{***} (0.146)	2.113^{***} (0.123)
Unemployment	0.849^{***} (0.051)	0.874^{***} (0.045)	-	0.798^{***} (0.048)	0.446^{***} (0.039)	0.342^{***} (0.033)
Prison	-0.030 (0.064)	0.050 (0.050)	-	-0.122^{***} (0.063)	-0.321^{***} (0.047)	-0.352^{***} (0.033)

Notes: Variables are expressed in log (see Eq. (9)). Prison deterrence measure is expressed as inmates prison admission per crime. Standard errors are in parenthesis. *,**,*** indicate significance at 10%, 5% and 1% level. The auto theft crime regression is not estimated when *prison* is considered, since cointegration test results are not statically significant (see Table 4).

Table 7: Estimation results of Equation (9), 1978-2013. Measure of inequality: Gini.

Variables	property	burglary	auto theft	larceny theft	violent	robbery
Gini	4.726^{***} (0.324)	2.611^{***} (0.288)	2.777^{***} (0.280)	4.788^{***} (0.306)	4.003^{***} (0.249)	2.115^{***} (0.215)
Unemployment	0.646^{***} (0.049)	0.760^{***} (0.043)	-0.013 (0.041)	0.572^{***} (0.048)	0.302^{***} (0.037)	0.230^{***} (0.032)
Police	-0.765^{***} (0.144)	-0.681^{***} (0.129)	-0.430^{***} (0.122)	-0.777^{***} (0.136)	-0.050 (0.112)	-0.506^{***} (0.096)
Variables	property	burglary	auto theft	larceny theft	violent	robbery
Gini	6.571^{***} (0.340)	4.586^{***} (0.291)	6.694^{***} (0.266)	6.730^{***} (0.323)	6.467^{***} (0.259)	5.003^{***} (0.211)
Unemployment	0.639^{***} (0.048)	0.699^{***} (0.043)	0.108^{***} (0.038)	0.571^{***} (0.045)	0.256^{***} (0.036)	0.157^{***} (0.029)
Prison	-0.281^{***} (0.063)	-0.247^{***} (0.049)	-0.607^{***} (0.040)	-0.321^{***} (0.065)	-0.467^{***} (0.049)	-0.468^{***} (0.033)

Notes: Variables are expressed in log (see Eq. (9)). Prison deterrence measure is expressed as inmates prison admission per crime. Standard errors are in parenthesis; *,**,*** indicate significance at 10%, 5% and 1% level.

5 Conclusions

This paper aims to estimate the long run relationship between crime, unemployment, inequality and deterrence in the US at state-level over the period 1978-2013 using non-stationary panels based on a common factor structure. We consider several measures of crime and deterrence and use a recently developed CUP estimator developed by Bai and Kao (2006) that controls for serial correlation and endogenity.

Our empirical analysis offers four main results. First, our crime model well fits the long run relationship between different type of crimes, inequality, unemployment and deterrence measures. Second, the impact of inequality and unemployment on crime is positive, whereas that of deterrence is negative. Third, crimes appear to be more sensitive to share of total income within a larger population. Fourth, the two measures of deterrence exert a similar effect on violent crimes, while police activities are more effective to combat property crimes.

Our empirical results induce some reflections on the effectiveness of measures to combat crime. First, policies aiming to sustain personal income of more disadvantaged people may help to weaken crime. Second, police enforcement activities may not produce a relevant reduction in violent crimes. Lastly, a reinforcement of imprisonment policy may be unsustainable in terms of social costs.

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A Data appendix

Data on crimes and prison admissions are taken from the Bureau of Justice Statistics, whereas data on police defense expenditures are from `http://www.usgovernmentspending.com/`. Data for unemployment rate are taken from US Bureau of Labour Statistics. Income inequality data are from Frank (2009) available at `http://www.shsu.edu/~eco_mwf/`.