The Economic Determinants of Crime: an Approach through Responsiveness Scores

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1 Introduction

In the last decades, crime has been a critical societal issue in the United States, and a topic of intensive research both in economics and other social sciences. After a steady and worrying rise of crime rates between the 1960s and 1980s, trends have been moving the opposite way since the 1990s (Kearney et al. (2014)).

There is no single cause identifying the different levels of crimes over time, as a number of determinants, often interacting, contribute to their variations. These may range from social to geographical and historical causes, and events whose effect is only indirect, but equally strong. For instance, Levitt & Dubner (2005) argue that the legalization of abortion throughout the country in 1973 has been critical in reducing crime rates in the following generation, and attribute this to the decrease in the birth rates among the most disadvantaged or unstable social categories.

Socioeconomic factors also play a major role by determining, for instance, the inclusion within one of these social categories, but also, as discussed in this paper, establishing incentives for engaging in crime. The issue with this type of setting is that most of the previous literature in the field have mainly analysed each driver individually, without necessarily providing a global account of the phenomenon. For econometrics follows. The main advantage of this technique is that it relaxes the classic assumption that each observation of the population has the same slope, thus allowing for idiosyncratic responses. Moreover, among the other features, it makes it possible to analyze factor accumulation returns, for the investigation on both the

Educational attainment;

Employment level;

Wage income;

Income inequality;

Public expenditure on police;

The presence of foreign born population.

We proceed by discussing some of the related literature for each of these factors.

after being unemployed for a short period people tend to look for another job, a long spell of unemployment increases the likelihood of criminal activity. The wage from legal activities matters both as a component of income, and as the opportunity cost of criminal actions. Concerning the first aspect, Buonanno (2003) highlights that both the income of the offender and that of the victim represent relevant factors, as the first is a cost while the second an incentive to commit crimes, thus leading to expect opposite signs of their effects.

Different studies have also led to believe that income inequality plays a critical role in determining crime levels. Buonanno (2003) highlights that income inequality can be thought as a measure of the differential between legal and illegal payoffs and İmrohoroğlu et al. (2006) identify it as one of the variables having the greatest effect on the crime rate. As explained by Kelly (2000), the direct effect of inequality is to juxtapose those with low returns from their legal activities and people with

& Vaughan (2009) stress several problems in terms of data collection and contrary results in the previous literature. Also, the answer to this question is likely to change according to the geographical area, its economic characteristics, the composition of its immigration pool, and their integration with the native population. Due to all these challenges, the literature on migration and crime is not as extensive as on the other determinants. Nevertheless, at least in the United States, racial inequality is still a dominant feature, and it has been widening with the Great Recession (Kochhar & Fry (2014)). This suggests an intrinsic disadvantage of being \di erent" that, again as in Merton (1938), might be manifested as a higher propensity to engage in criminal activities.

3 Data and methodology

3.1 Data and variables description

The dataset is a panel constructed for 50 US states[2] for the period 2000{2012. Data for the demographic and microeconomic variables are an elaboration from the Amer-

Responsiveness scores (RS) measure the change of a given outcome y when a given factor x_j; (j

$\mathbf{x}_{i;\ j}$). Observe that $_0$ and $_0$ are, on the contrary, constant parameters. According to this model, we can de ne the regression line as:

$$E(y_i|x_{ij};\mathbf{x}_{i;\ j}) = E(a_{ij}|\mathbf{x}_{i;\ j}) + x_{ij}\ \ E(b_{ij}|\mathbf{x}_{i;\ j}) \tag{4}$$

Given this, we de ne the *responsiveness* e ect of x_{ij} on y_i as the derivative of y_i respect to x_{ij}, that is:

$$\frac{\partial}{\partial x_{ij}}[E(y_i|x_{ij};\mathbf{x}_{i;\ j})] = E(b_{ij}|\mathbf{x}_{i;\ j}) \tag{5}$$

where $E(b_{ij}|x_{ij};\mathbf{x}_{i;\ j})$ is the partial e ect of x_{ij} on y_i. We can repeat the same procedure for each x_{ij} (with $j = 1;:::;Q$) { so that it is eventually possible to de ne, for each unit i=1,..., N and factor $j = 1;:::;Q$, the $N\ \ Q$ matrix B of the partial e ects as follows:

$$\mathrm{B} = \begin{pmatrix} E(b_{11}|\mathbf{x}_{i;\ j}) & \cdots & E(b_{1Q}|\mathbf{x}_{i;\ j}) \\ \vdots & E(b_{ij}|\mathbf{x}_{i;\ j}) & \vdots \\ E(b_N^{E}\ \ _{i;\ j} \end{pmatrix}$$

[redacted]

Once these regression parameters are estimated, we can obtain an estimate of the partial effect of factor x_j on y for unit i as:

$$\hat{E}(b_{ij}|\mathbf{x}_{i;-j}) = \hat{\gamma}_0 + \mathbf{x}_{i;-j}\hat{\boldsymbol{\gamma}} \tag{8}$$

By repeating this procedure for each unit i and factor j, we can finally obtain $\hat{\mathbf{B}}$, i.e. the estimation of matrix $\mathbf{B}$.

When a longitudinal dataset is available, the estimation of $\mathbf{B}$ can be obtained either by using random-effects or fixed-effects estimation of the following panel data regression:

$$y_{it} = \alpha_0 + \mathbf{x}_{i;-j;t}\boldsymbol{\alpha} + (\gamma_0 + \bar{\mathbf{x}}_{-j;t}\boldsymbol{\gamma})x_{ijt} + x_{ijt}(\mathbf{x}_{i;-j;t} - \bar{\mathbf{x}}_{-j;t})\boldsymbol{\gamma} + \mu_i + \epsilon_{it} \tag{9}$$

where the added parameter μ_i represents a unit–specific effect accounting for unobserved heterogeneity. In particular, fixed–effect estimation, by allowing for arbitrary correlation between μ_i and ϵ_{it}, can mitigate a potential endogeneity bias due to misspecification of previous equation and measurement errors in the variables considered in the model (Wooldridge 2010, pp. 281–315). As such, a panel dataset may allow for more reliable estimates of the responsiveness scores than OLS estimates on a cross-section.

If the variables are standardized, eq. (9) becomes:

$$y_{it} = \alpha_0 + \mathbf{x}_{i;-j;t}\boldsymbol{\alpha} + \gamma_0 x_{ijt} + x_{ijt}\mathbf{x}_{i;-j;t}\boldsymbol{\gamma} + \mu_i + \epsilon_{it} \tag{10}$$

which simplifies the formula.

Finally, following Eq. (8), the variance of the propensity score can be found to be equal to:

$$\widehat{Var}\left[\hat{E}(b_{ij}|\mathbf{x}_{i;-j})\right] = \widehat{Var}(\hat{\gamma}_0) + \mathbf{x}_{i;-j}^2\widehat{Var}(\hat{\boldsymbol{\gamma}}) + 2\cdot\mathbf{x}_{i;-j}\cdot\widehat{Cov}(\hat{\gamma}_0;\hat{\boldsymbol{\gamma}}) \tag{11}$$

that allows us to compute, for each single score, the statistical significance at the three commonly considered levels of 1% , 5%, and 10%. For the sake of simplicity, we report here for each factor just a "rate of significance", i.e. the share of responsiveness scores significant *at least* at the 10% level.

4 Results

Table 1 shows that the R-squared statistic is particularly high for all factors, ranging from 0.69 to 0.73, with a mean of 0.71. The same is true for the category of property crimes, although the average R-squared drops to about 0.49 when using the ratio of violent crimes over population as the dependent variable. Nevertheless, this shows a reasonable goodness of fit, so we are confident that our coefficients take account of important correlations in the data. Moreover, the significance rate is particularly high (93%) for the factor *Police* and around 50% for *Education*, *Foreign born* and *Inequalities*. On the other hand, the factors *Employment* and *Wage* exhibit lower shares of scores significant at least at the 10% threshold (23% and 29% respectively). When separately analyzing the two types of crimes, significance rates are not dissimilar from the aggregate ones in the case of *Police* and *Foreign born*, while generally more elevated for violent crimes rather than property crimes (with the exception of *Inequality*).

Dependent variable	Mean R^2	Factors	Significance rate
Total crime	0.71	Education	0.55
		Employment	0.23
		Police	0.93
		Inequality	0.47
		Wage	0.28
		Foreign born	0.54
Violent crime	0.49	Education	0.62
		Employment	0.39
		Police	0.92
		Inequality	0.33
		Wage	0.42
		Foreign born	0.54
Property crime	0.71	Education	0.55
		Employment	0.19
		Police	0.92
		Inequality	0.47
		Wage	0.31
		Foreign born	0.52

Table 1: Summary table for the R-squared statistics and the Significance rate.

We proceed by presenting our results in the following order. First, we comment on the distribution of the responsiveness scores and on some descriptive statistics; second, we move to a graphical study of the factor returns, in order to assess whether

Figure 1: Distribution of the responsiveness scores over the period 2000-2012.

di erent levels of a factor can in uence the responsiveness of crime rates. Third, we perform a brief analysis by aggregating our observations in sub{national units; and nally, we disaggregate our crime measure in order to account for di erential e ects depending on the type of crime (i.e., property and violent).

4.1 Distribution of the responsiveness scores

The responsiveness scores approach allows to perform a series of additional analyses, ranging from the representation of their distributions and basic descriptive statistics to the study of the single idiosyncratic responses to the factors. Figure 1 shows the

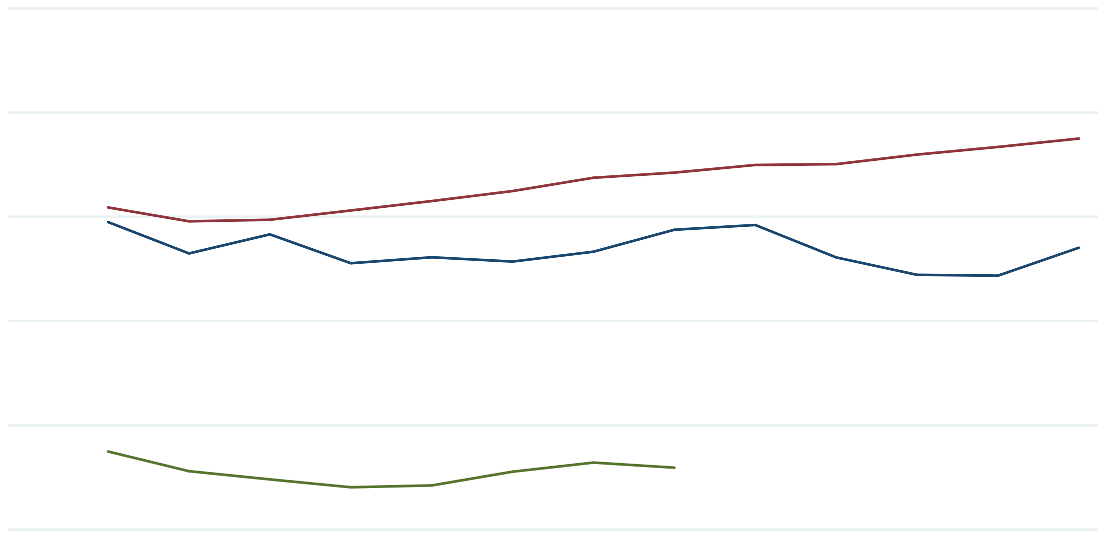

Figure 2: Timepaths of the responsiveness scores for the period 2000{2012.

household income, or income per capita. In this case, as explained by Buonanno (2003), there could be a higher potential gain (the victims' income) from certain kinds of crime, and speci cally property crime (Fleisher (1966)).

Finally, crime has a predominantly positive responsiveness to the share of *Foreign born*. Although this is true on average, and for most of the observations, for a small part of them the opposite is true. We conclude that the direction of the impact of immigrants on crime critically depends on the level of immigrants' integration among the native population. This, on turn, could re ect di erent levels of education and income within the foreign community. Moreover, as mentioned in Section 2, a big part of the story may be the dominant incidence of poverty among immigrants, and especially non-white. This inevitably brings us back to the issue of income inequality, to which this share of the population tends to be the most a ected.

4.2 Returns to scale

di erent levels of diversity interact with the responsiveness to education. The relation is unambiguously negative, with the e ect of education on crime decreasing and soon becoming negative for higher levels of the diversity index. At the same time, if the diversity index only proxies for the amount of foreign born, this could also be a sign of the higher level of schooling attainment among the most disadvantaged social categories (which, as mentioned before, often happen to be the non-whites): increased education for this share of the population, where the initial level would most likely be lower than average, and which, because of its economic condition, might be particularly engaged in illegal activities, could therefore lead to reduced crime rates.

Figure 4: Factor accumulation returns for *Employment*.

The representation of the returns for *Employment* (Figure 4), which appear to be bell-shaped, is also of interest. The responsiveness score stays negative for most of the levels of the employment rate, but begins with increasing returns, reaches a peak where employment actually seems to increase crime, and then decreases again to negative values.

more than proportional. Again, the fact that foreign born population is on average more economically disadvantaged brings us back to the economic components of the analysis, which in turn might make the foreign born more prone to engage in crime.

Figure 5: Factor accumulation returns for *Police*, *Wage*, *Inequality* and *Foreign born*.

4.3 Geographical patterns

Another interesting feature that we can employ by working with responsiveness scores is the possibility of using the idiosyncratic e ect of the factor variables on the independent one at the individual unit (or state) level. This allows us to investigate connections and interactions among factors through di erent aggregations of these units. We performed a geographical analysis by dividing our sample into the four Census regions (West, Midwest, Northeast and South) thus evaluating their average responsiveness scores over the sample period contrasted with the overall mean for the US. As we can see in Figure 6, the subsets present behavior that are very similar to the macro trends except for two considerable outliers. First of all, we can easily see from the graph that the Midwest area, with its particularly high responsiveness score for *Education*, is the one raising the average and making the overall effect positive, as it otherwise would be negative for the other regions). Second, the West has a clear spike at the *Foreign born* corner, that points to a much greater response of crime to immigrants for this area. The questions that comes naturally is: what might be creating these anomalies?

Exploring our data, we find that 75% of the states in the Midwest are ranked below average when units are ordered according to their average Gini coefficient, i.e. income tends to be more fairly distributed. On the basis of the literature, a possible hypothesis would therefore be that, suffering less from inequalities, crimes that are mainly due to resentment and social tensions (Merton (1938)), as violent crimes, are less common, with possibly more property crime. According to Buonanno & Leonida (2005*b*) and Abdullah et al. (2015) education has the effect of reducing income inequality. Thus, a lower Gini index could be signalling for higher education level, which in turn points to a greater likelihood of committing property crimes. As for the case of the West region, performing a similar exercise, all of the eleven states in the subsample appear in the second half of the ranking, with eight being among the lowest ten. It is clear that we are now considering the poorest units of the sample: we could for instance presume a hostile attitude of the natives, because of the adverse economic situation, towards immigrants, that makes crime more reactive to the share of foreign born. Another possibility, is that being the states relatively poor, new immigrants will more likely be poor as well, and typically poorer than the natives, thus triggering social conflict and then crime.

As a last step, we also report the same kind of results for the ten states with the highest crime rate (Figure 7) as well as for the lowest ten (Figure 8). Except for a few states departing from the mean, the two graphs are characterized by distinct shapes. For the units with the highest crime rates, the values are very similar to those of the overall US average, with a particular high incidence of the *Foreign born* factor. On the other hand, for the states with low crime rates, the responsiveness to *Education* and *Inequality* is on average extremely high, while the effect of *Police* tends to be lower in magnitude. While the first fact could be explained through economic differences, the second set of findings is less comprehensible. We could suppose that, where the crime level is low, changes in *Education* and *Inequality* produce a greater shock to the dependent variable, thus causing responsiveness to be higher. At the same time, as

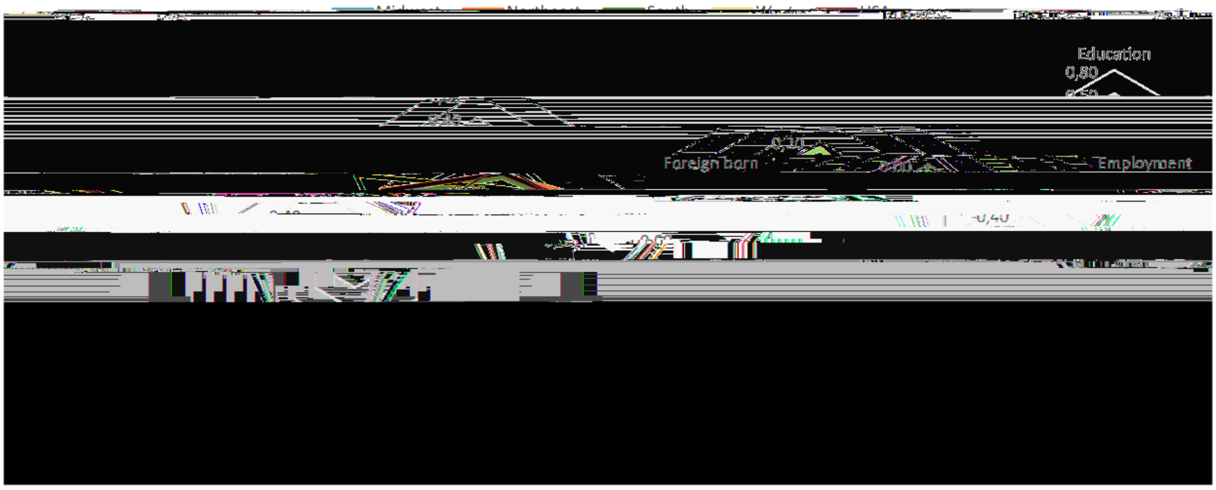

Figure 6: Incidence of factors by regions.

illegal activities are not predominant, an increase in the expenditure for police does not cause crime to fall as much as it would be in higher crime contexts. Moreover, the crime rate could already be low because of the prevalence of policing which lowers the e ect of additional units of the same factor.

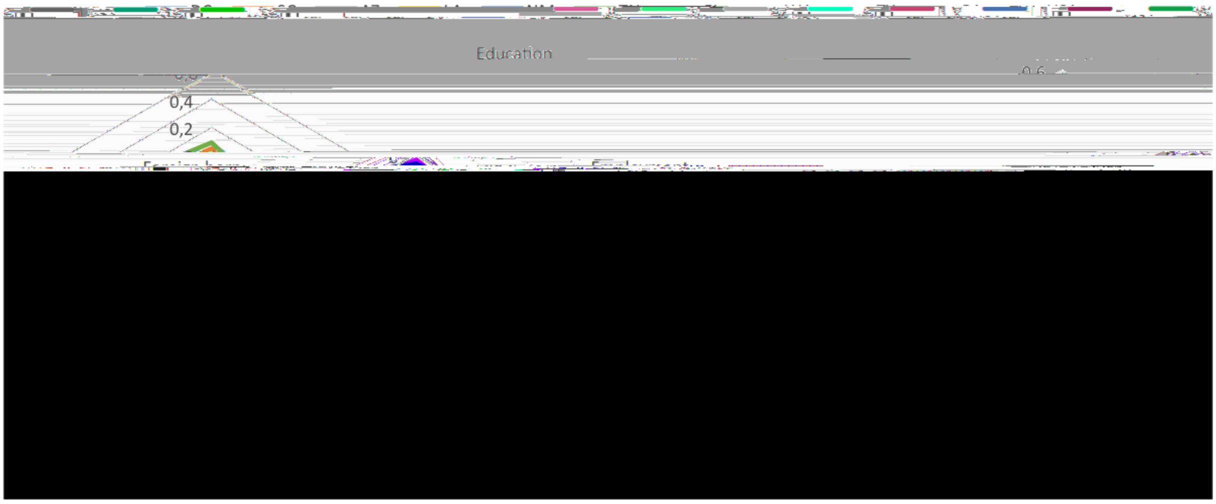

Figure 7: Incidence of factors in the highest 10 crime rate states.

4.4 Violent vs. Property crimes

We move now to testing whether our hypotheses on the existence of di erent e ect depending on the type of crime are actually con rmed by the data. The FBI Uniform

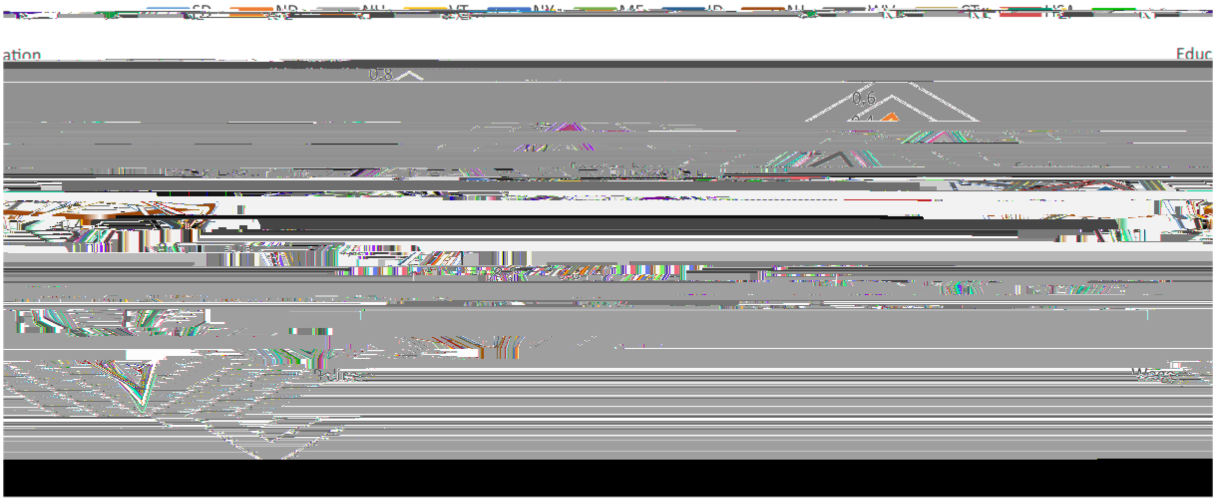

Figure 8: Incidence of factors in the lowest 10 crime rate states.

Crime Reports program (U.S. Federal Bureau of Investigation (2010*b*,*a*)) only distinguishes crimes according to the type of o ense: *violent crime* or *property crime*. For the rest of the analysis, we will assume that the category of \white collar crimes" are mostly included in property crimes[8].

aspects. While property crimes' responsiveness scores generally appear to have an almost constant mean over time, violent crime varies more across years. In particular, all factors but employment show decreasing trends. Moreover, responsiveness scores for violent crime are in general smaller in absolute value.

Figure 9: Time trends for (a) violent crime; (b) property crime.

We also repeated the exercise on both variables for the factor returns analysis. First, we look at the Education factor, whose graphical representation is in Figure 10. Plotting the responsiveness scores for Education over the average years of the same factors produces graphs that are similar in their slightly decreasing shape, but that also present a crucial di erence. For violent crimes, responsiveness is always negative and increasing in absolute value for the highest levels of education. However, they turn from positive to negative in the case of property crimes. In other words, in the case of property crime, increasing education from a low level of schooling increases crime, while moving to higher average education the e ect has the opposite sign. Again, this could be taken as evidence of the presence of white collar crimes within our broader category: skills acquired through education are initially complementary to crimes as fraud or embezzlement. However, the benefits that very high levels of education can provide increase the opportunity cost of committing crime, thus inverting the tendency.

Moreover, when we examine the relationship between scores for education and cultural diversity for the two categories of crime, it is clear that the overall decreasing correlation shown in Section 4.2 is mainly driven by violent crimes. This clear pattern would suggest that, for increasing levels of cultural diversity, raising education has a greater effect on reducing violent crime, while its impact on property crime is smaller.

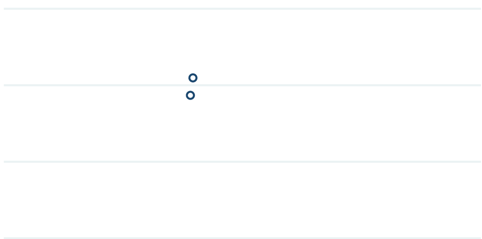

Figure 10: Factor accumulation returns for *Education*.

Moving now to the returns for *Employment*, Figure 11 presents us with a few points of interest, although the differences are not as significant as for *Education*. The inverse U-shaped relation we have seen above is now particularly evident in the case of property crimes, suggesting an increase in responsiveness due to the presence of more skilled and able workers, and a following reduction, possibly connected to a higher opportunity cost of losing the job if caught. On the other hand, the interacted effect with our measure of inequalities reveals a positive correlation for both contexts, although responsiveness turns from negative to positive in the case of property crimes. Following the reasoning proposed in Section 4.2, we suggest the hypothesis that increases in the employment rate for high level of inequality would mainly benefit those at the top of the distribution, triggering hostility and thus violent crimes. The logic

obtained should indeed be read as *scores*, i.e., descriptive measures of the level of responsiveness. Moreover, although we have chosen to work with state level data, an analysis at a more micro level could possibly reveal some more interesting results. Nevertheless, we believe that this paper and its new empirical approach, adds to our understanding of the factors related to crime in at least three significant ways. First of all, we are able to relax the assumption of coefficients being constant over observations. This allows us to estimate the impact of each determinant individually, perform geographical analysis and aggregate units according to different principles and ranking in order to have a better understanding of the phenomenon. Secondly, given that all the values are standardized, we can establish a unequivocal ordering of the factors in terms of their importance in affecting crime. Finally, the paper provides an example of the plausibility of the method of responsiveness scores in the field of

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Appendix

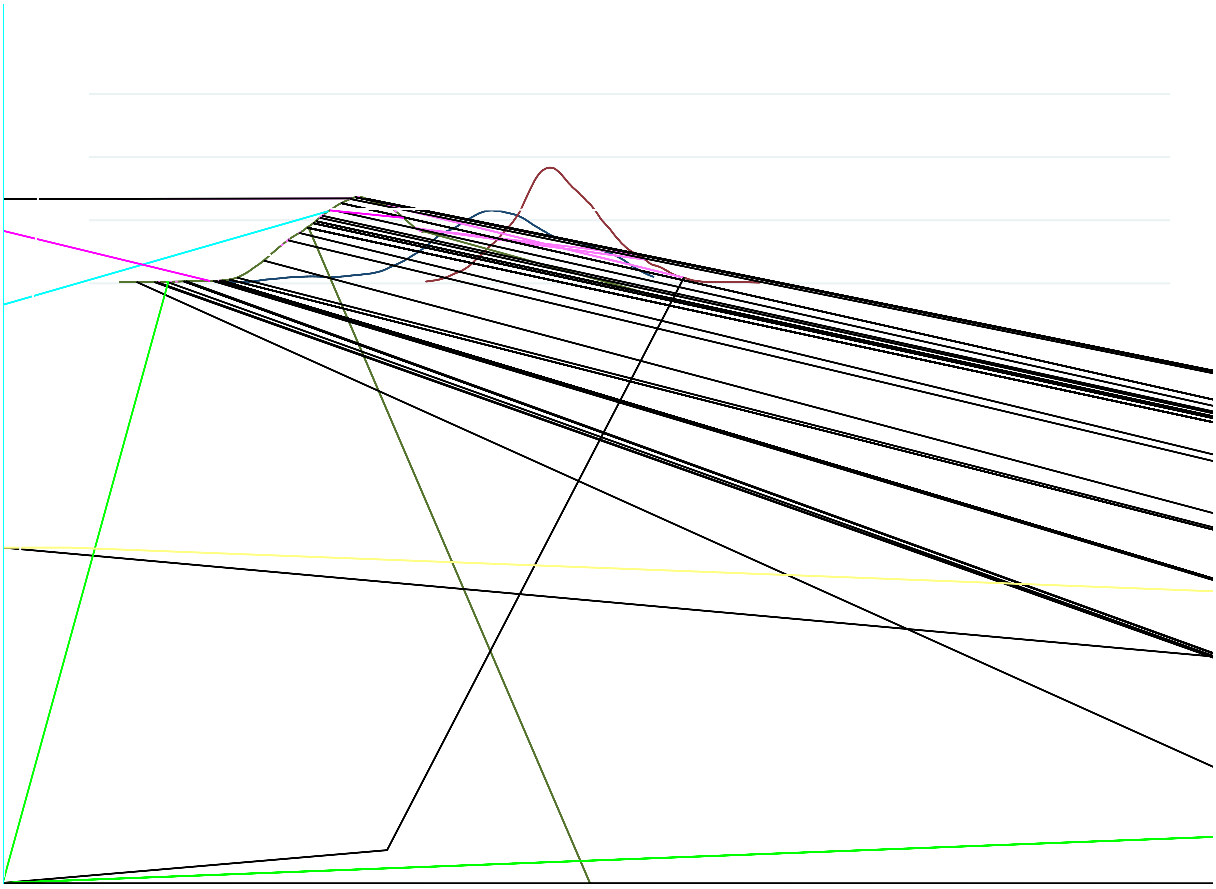

Figure 13: Distribution of responsiveness scores for (a) violent crime; (b) property crime.

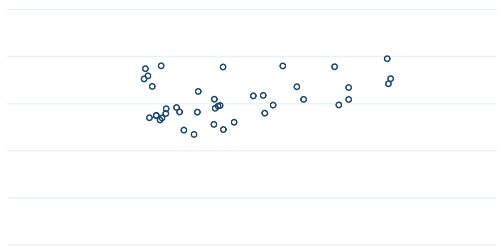

Figure 14: Factor accumulation returns for *Employment*.