The Economic Determinants of Crime:
an Approach through Responsiveness Scores

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Abstract

Criminality has always been part of human social interactions, shaping the way peoples have constructed states and legislation. As social order became a greater concern for the public authorities, interest in investigating incentives pushing individuals towards engaging in illegal activities has become a central issue of the political agenda. Building on the existing literature, this paper proposes to focus on a few primary determinants of crime, whose effect is investigated using a Responsiveness Scores (RS) approach performed over 50 US states during the period 2000–2012. The RS approach allows us to account for unit heterogeneous response to each single determinant, thus paving the way to a more in-depth analysis of the relation between crime and its drivers. We attempt to overcome the limitations posed by standard regression methods, which assume a single coefficient for all determinants, thus contributing to the literature in the field with stronger evidence on determinants' effects and the geographical patterns of responsiveness scores.

Keywords: Crime, Incentives, Responsiveness Scores
JEL Classification: K42, J24, P46

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 instance, Lochner (2004) focused on the role of education, while Fowles & Merva (1996) focus on the effect of changes in the distribution of wage income. Although an intensive knowledge of each single factor can definitely offer some critical insight, we believe that gathering the main determinants and observing how those interact in an inclusive context should result in more realistic scenarios that would reflect society in all its aspects. Clearly, performing a multiple regression, with the factors of interest as independent variables, would be the most common way to proceed in order to respond to the research question and look at possible causality links. However, this standard approach contains the obvious limitation of assuming that coefficients are identical across units and time, thus ignoring potential heterogeneity in the impact of the factors, whose effects are likely to vary according to the geographical and historical framework.

Therefore, we choose instead to adopt the method of responsiveness scores, whose successful application by Cerulli (2014) in the field of technological innovation has raised the possibility for its use in different fields. Responsiveness scores are based on an iterated Random Coefficient Regression model (Wooldridge (2010)) for each unit and for each factor. A more detailed and technical description of the underlying

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 same factor and a cross-partial effect of other determinants. Hence, our aim is to enhance the existing literature by adding a study of the overall dynamics of the main drivers of crime, as identified and discussed by other authors, in all their complexity, heterogeneity, and interaction.

The rest of the paper is organized as follows. Section 2 presents an overview of the theoretical framework, while Section 3 presents a brief explanation of the method of responsiveness scores and describes the data. Section 4 shows the main results and provides a rationale, based on past research, for the obtained outcomes while Section 5 concludes.

2 Theoretical background of the determinants of crime

The causes of crime have been widely studied by social sciences, with economic determinants acquiring greater relevance during the last decades. Although the analysis of the effect of income on delinquency was not new to the field (e.g., Fleisher (1966)), this stream of modern literature was pioneered by Becker (1968). In his seminal paper, he presents the criminal's choice, intended as the main trigger of the "supply of offenses," as a standard microeconomic problem of expected utility: the individual chooses whether to commit a crime by comparing its expected benefits with its costs, which also can include the loss of an outside option, usually represented by income from a legal, and less risky, activity. He also introduces the theme of punishment of crime, which enters the problem both in the forms of probability of being caught and magnitude of the penalty. Ehrlich (1973) refines and extends this model, and gives a greater twist to the discussion of the responsiveness of individuals to economic incentives and to their interaction. In this context, many other factors besides individual income can be included in the analysis of the determinants of crime, as they modify people opportunities in legal activities, and therefore their expected returns from engaging in offenses. Here, we choose to consider six main drivers analyzed in previous studies which are likely to be correlated to other omitted factors. They are:

- 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.

Education can impact the incidence of crimes in several ways. Machin et al. (2011), among others, extensively discuss three main channels. Through income effects, education increases expected wages, and therefore the returns from legitimate work, increasing the opportunity cost of crime. Following this idea, most scholars would predict a decrease in criminal activity for an increase in education, although Levitt & Lochner (2001) find that certain mechanical knowledge and related disciplines can improve chances in the criminal world. Resources allocated to education also create time constraints that should work in keeping teenagers away from committing offenses. Witte & Tauchen (1994) find that greater time spent in school is correlated with a lower probability of criminal activity. Moreover, a stream of literature also associates greater education with higher life satisfaction, as in Oreopoulos (2007) and Lochner (2004) finding that higher levels of education increase patience and risk aversion, thus lowering crime.[1] Usher (1997) considers a fourth channel, a civic externality of education, which is assumed to affect one's willingness to commit an offense. In general, we would therefore expect a negative relation between educational attainment and crime.

Labor market conditions have also been widely used to motivate different incidence of crime. Although employment status has been prevalent in the early literature, with Fleisher (1963) establishing a positive effect of unemployment on delinquency, modern works have rather focused on the pecuniary aspect of labor market. Gould et al. (2002) remark that, as employment is highly cyclical, it can hardly explain a long-term trend in crime, as observed in the United States. Moreover, Gumus (2003) distinguishes between short-term and long-term effects of unemployment, and concludes that while

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[1]The attitude toward risk is a factor that Becker (1968) also takes into consideration in his model.

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 İmrohoroĝlu 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 considerably higher wealth. A second consequence of inequality is explicated by the strain theory of Merton (1938), who argues that because of the same juxtaposition of social classes, frustration of the poorest individuals could represent a triggering motive for criminal activity. In both cases, the impact of inequality should then lead to higher crime rates.

Police presence and public expenditure in protection has also claimed a relevant impact on crime. The topic is extensively discussed by Levitt & Dubner (2005): although recognizing that there may be simultaneity bias, as police presence action affects crime trends, but also a higher crime rate will call for higher police protection. They provide some interesting evidence of an inverse effect of police on crime by using exogenous changes in the number of police around the time of elections to find that additional police can lower the crime rate. On the other hand, by looking at the significant crime decline of the 1990s in the United States, they also show that innovative police strategies had a more limited effect. Draca & Machin (2015) note that the effect of policing is oriented towards a deterrence mechanism, which enters the framework outlined in Becker (1968) by decreasing the expected returns from crime. Di Tella & Schargrodsky (2002) partly confirm this suspected negative effect by using a natural experiment to find the effect of larger police forces on car theft.

Finally, Buonanno (2003) highlights the importance of social interactions and social networks among the determinants of crime. This raises the issue of immigration, whose link with criminality has always been rather controversial. Camarota

& 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 "different" 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 American Community Survey (ACS) microdata available from IPUMS USA, and we used the 2010 Consumer Price Index to deflate nominal measures. Measures of public expenditure on police forces have been retrieved from the US Census Bureau Government Finances section, and the Gini Index for the states is calculated by the Economic Department of Houston State University. The outcome variable is represented by a crime rate of a state s in a given year t. This is constructed as

$$crime_{st} = \frac{VC_{st} + PC_{st}}{Pop_{st}}$$

where VC_{st} is the number of violent crimes[3] for the unit observation and PC_{st} the number of property crimes[4] for the same, and the denominator Pop_{st} the total population of the state at that time. Data on crime in the US is available through the FBI Uniform Crime Reporting System database, and it has been aggregated from

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[2]Hawaii is not included as it doesn't participate to the FBI Uniform Crime Reporting Program. We include the District of Columbia (DC).

[3]The FBI UCR program defines "Violent crimes" as "those offenses which involve force or threat of force", including murder and nonnegligent manslaughter, forcible rape, robbery, and aggravated assault (U.S. Federal Bureau of Investigation (2016b)).

[4]"Property crimes" are those with the object of "taking of money or property, but there is no force or threat of force against the victims", and include burglary, larceny-theft, motor vehicle theft, and arson (U.S. Federal Bureau of Investigation (2016a)).

the agency level data. For each state and year of observation, we consider six factor variables in order to construct responsiveness scores:

- *Education*: average school attainment for the population;

- *Employment*: employment rate calculated as ratio of employed workers over working age population (15–65 years old);

- *Police*: total amount of state government expenditure in police protection;

- *Inequality*: as represented by the Gini coefficient of income inequality;

- *Wage*: average wage and salary income for the population;

- *Foreign born*: ratio of foreign born over total population.

All the factor variables have been lagged one year, in order to account for possible delayed effects. Moreover, an indicator for the political orientation of the state (red or blue) is used as a control variable. Later in the analysis, measures of total household income, and a diversity index constructed as in Ottaviano & Peri (2006)[5] are also used in order to rank the states and investigate the aforementioned effects for given categories.

3.2   The responsiveness scores approach

As explained above, the investigation of the socioeconomic determinants of crime is not new to the literature. In this paper, however, we propose a new type of analysis based on the Responsiveness Scores technique as proposed by Cerulli (2014, 2017). The main advantage of this approach is that it allows for heterogeneous responses of the macro units of observation to the factor variables. In what follows, we set out a concise methodological account of this method.

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[5]The index is constructed as the probability that two individuals that are randomly drawn from the population of the state are born in the same country: $DI_{st} = 1 - \sum_{i=1}^{M} \left(\frac{CoB_{ist}}{TP_{st}} \right)^2$, where CoB_{ist} is the number of residents born in country i; TP_{st} is the total population of the state; and M is the number of different cultural groups that are potentially present in the state.

Responsiveness scores (RS) measure the change of a given outcome y when a given factor $x_j, (j = 1, \ldots, Q)$ changes, conditional on the other $(Q - 1)$ factors:

$$\mathbf{x}_{-j} = [x_1, \ldots, x_{j-1}, x_{j+1}, \ldots, x_Q]. \tag{1}$$

Algebraically, it is the derivative of y on x_j, given $\mathbf{x}_{-j}$, when one allows for each observation to have its own responsiveness score. We assume that $\mathbf{x}_{-j}$ is a vector of all exogenous variables. RS are obtained by an iterated random–coefficient regression (RCR), whose basic econometrics can be found in (Wooldridge 2010, pp. 141–145).

The calculation of RS follows this simple protocol:

1. Define y, the outcome (or response) variable.

2. Define a set of Q factors thought of as affecting y, and indicate the generic factor with x_j.

3. Define a RCR model linking y to the various x_j, and extract a unit–specific responsiveness effect of y to all set of factors x_j, with $j = 1, \ldots, Q$.

4. For the generic unit i and factor j, indicate such effect as b_{ij} and collect all of them in a matrix $\mathbf{B}$.

5. Finally, aggregate by unit (*row*) and/or by factor (*column*) the $\mathrm{E}(b_{ij}|\mathbf{x}_{i,-j})$ thus getting synthetic unit and factor responsiveness measures.

Analytically, a RS is the "partial effect" of a factor x in a RCR (Wooldridge, 1997; 2003; 2004). Indeed, for each $j = 1, \ldots, Q$, define a RCR model of this kind:

$$\begin{cases} y_i = a_{ij} + b_{ij}x_{ij} + e_i \\ a_{ij} = \gamma_0 + \mathbf{x}_{i,-j}\gamma + u_{ij} \\ b_{ij} = \delta_0 + \mathbf{x}_{i,-j}\delta + v_{ij} \end{cases} \tag{2}$$

where e_i, u_{ij} and v_{ij} are freely correlated error terms with:

$$E(e_i|\mathbf{x}_{i,-j}; x_{ij}) = E(u_{ij}|\mathbf{x}_{i,-j}; x_{ij}) = E(v_{ij}|\mathbf{x}_{i,-j}; x_{ij}) = 0 \tag{3}$$

It is easy to see that the regression parameters, a_{ij} and b_{ij}, are both non-constant as they depend on all the other inputs x except x_j due to the definition of the vector

$\mathbf{x}_{i,-j}$). Observe that δ_0 and γ_0 are, on the contrary, constant parameters. According to this model, we can define the regression line as:

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

Given this, we define the *responsiveness* effect 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 effect 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 define, for each unit $i=1,..., N$ and factor $j = 1, ..., Q$, the $N \times Q$ matrix $\mathbf{B}$ of the partial effects as follows:

$$\mathbf{B} = \begin{pmatrix} E(b_{11}|\mathbf{x}_{i,-j}) & \dots & E(b_{1Q}|\mathbf{x}_{i,-j}) \\ \vdots & E(b_{ij}|\mathbf{x}_{i,-j}) & \vdots \\ E(b_{N1}|\mathbf{x}_{i,-j}) & \dots & E(b_{NQ}|\mathbf{x}_{i,-j}) \end{pmatrix} \tag{6}$$

If all variables are standardized with zero mean and unit variance, partial effects are *beta–coefficients*, thus independent of the unit of measurement. As such, they can be compared with each other and summed[6].

In a cross–section data setting, Ordinary Least Squares (OLS) provides consistent estimation of each b_{ij} within this regression[7]

$$\begin{aligned} y_i &= \gamma_0 + \mathbf{x}_{i,-j}\gamma + (\delta_0 + \bar{\mathbf{x}}_{-j}\delta)x_{ij} + x_{ij}(\mathbf{x}_{i,-j} - \bar{\mathbf{x}}_{-j})\delta + \eta_i \\ \eta_i &= u_{ij} + x_{ij}v_{ij} + e_i \end{aligned} \tag{7}$$

where $\bar{\mathbf{x}}_{-j}$ is the vector of the sample means of $\mathbf{x}_{i,-j}$.

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[6]As beta-coefficients are measured in standard deviation units, they can be compared. The meaning of a beta-coefficient is straightforward: suppose that in a regression of y on x the beta is found to be equal to 0.3, then it means that one standard deviation increase in x leads to a 0.3 standard deviation increase in the predicted y with all the other variables in the model held constant.

[7]Indeed, OLS estimates are consistent as for each $j = 1, \ldots, Q$ we have $E(\eta_i|\mathbf{x}_{ij}) = E(u_{ij}|\mathbf{x}_{ij}) + x_{ij} \cdot E(v_{ij}|\mathbf{x}_{ij}) + E(e_i|\mathbf{x}_{ij}) = 0$. However, as η_i is clearly heteroskedastic, a robust VCE is necessary to produce consistent standard errors.

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:

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

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:

$$y_{it} = \gamma_0 + \mathbf{x}_{i,-j,t}\gamma + (\delta_0 + \bar{\mathbf{x}}_{-j,t}\delta)x_{ijt} + x_{ijt}(\mathbf{x}_{i,-j,t} - \bar{\mathbf{x}}_{-j,t})\delta + \alpha_i + \eta_{it} \tag{9}$$

where the added parameter α_i represents a unit–specific effect accounting for unobserved heterogeneity. In particular, fixed–effect estimation, by allowing for arbitrary correlation between α_i and η_{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:

$$y_{it} = \gamma_0 + \mathbf{x}_{i,-j,t}\gamma + \delta_0 x_{ijt} + x_{ijt} \cdot \mathbf{x}_{i,-j,t}\delta + \alpha_i + \eta_{it} \tag{10}$$

which simplifies the formula.

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

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

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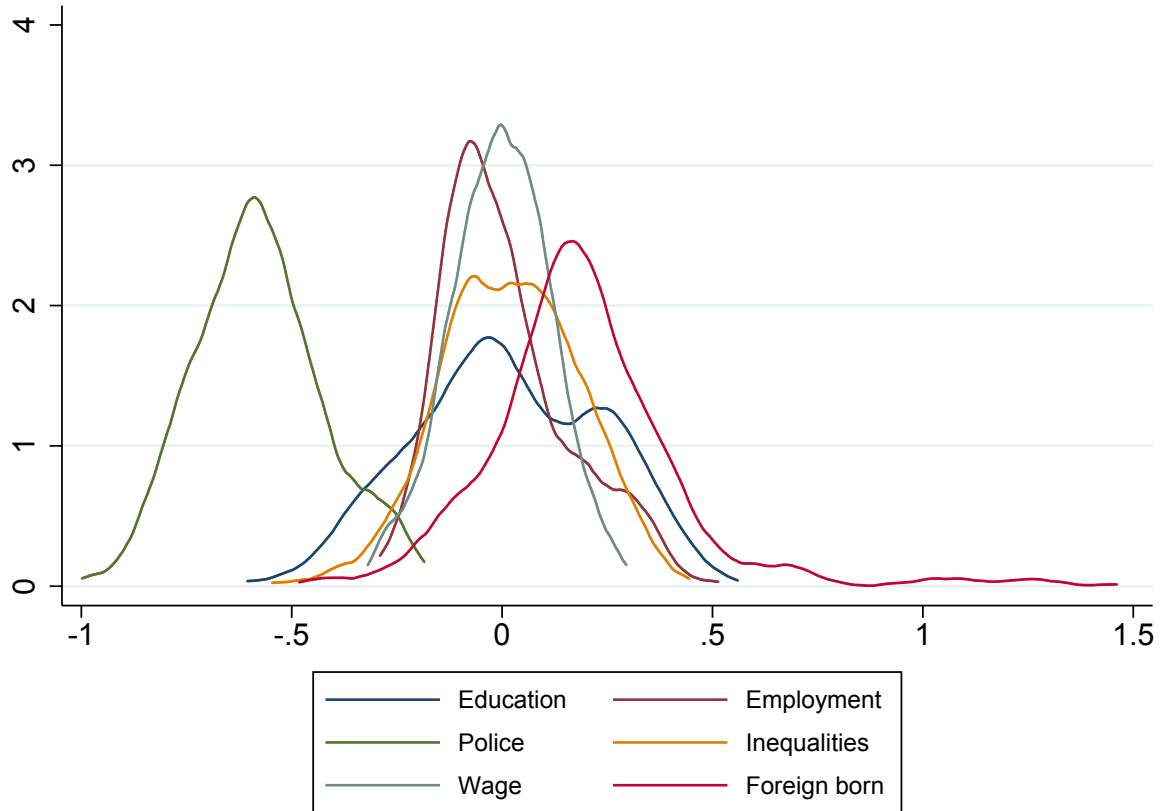
Figure 1: Distribution of the responsiveness scores over the period 2000-2012.

different levels of a factor can influence the responsiveness of crime rates. Third, we perform a brief analysis by aggregating our observations in sub–national units; and finally, we disaggregate our crime measure in order to account for differential effects 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 first analysis, regarding the distribution of the responsiveness scores for the different factors, while Figure 2 shows the time trends for the annual scores averages. The former allows us to rank the factors according to the magnitude of their effects. We can also assess the volatility of this effect by looking at the standard deviation.

We find that *Education* has, on average, a weak but clearly positive effect. This at

first might seem counterintuitive, although it is consistent with some of the literature. Buonanno & Leonida (2005a), while studying the impact of education on crime in Italian regions, conclude that there are non-linearities in the effect of education on crime. That is, crime decreases with the increase of education when the latter is low, but rises when it's already high. This seems to be correlated with the predominance, in high educated and richer areas of different kind of crime, namely there is a significant positive relation between fraud (a "white collar crime") and education. Thus, given the relatively high average level of educational attainment in the US, it would make sense to find a positive responsiveness of crime to education.

Moving on with the factors, the average responsiveness to *Employment* appears very close to zero (with a negative median), and not very volatile. Again, despite disagreeing with the earlier literature, this would still seem consistent, as mentioned in Section 2, with the line of research claiming little impact of unemployment on crime. Moreover, empirical evidence suggests that the job finding rate is particularly high in the US, and explains much of the cyclicality in unemployment (Shimer (2005)). If spells of unemployment are short, it is likely that shocks in this variable may not have a significant effect on crime.

The *Police* factor shows one of the most relevant scores, with no ambiguity in its sign. It is negative at any point of the distribution with a magnitude that ranges in absolute value between 0.18 and 0.99. This would mean that in some states, a variation of one standard deviation in the expenditure for police protection leads to a variation in the crime rate that is very close to proportional. Although subject to the usual difficulty in establishing a causal connection, we would tend to confirm the idea of a greater presence of police as a deterrent to criminals, but the topic will be further explored with the analysis of factor accumulation returns.

Moving to the *Inequality* variable, this also appears to have a weak, but on average positive effect, meaning that crime will respond positively to an increase in the Gini Index, i.e., an increase in income inequality. This is in line with the literature, and probably one of the most compelling results.

Wage, on the other hand, shows quite a heterogeneous effect. The distribution is almost symmetric around zero so, again, the mean coefficient is not very relevant in magnitude. Both the mean and the median are negative, thus corroborating the idea of wage as the opportunity cost of crime, and therefore negatively correlated with it. At the same time, in certain situations a higher wage income could reflect a higher
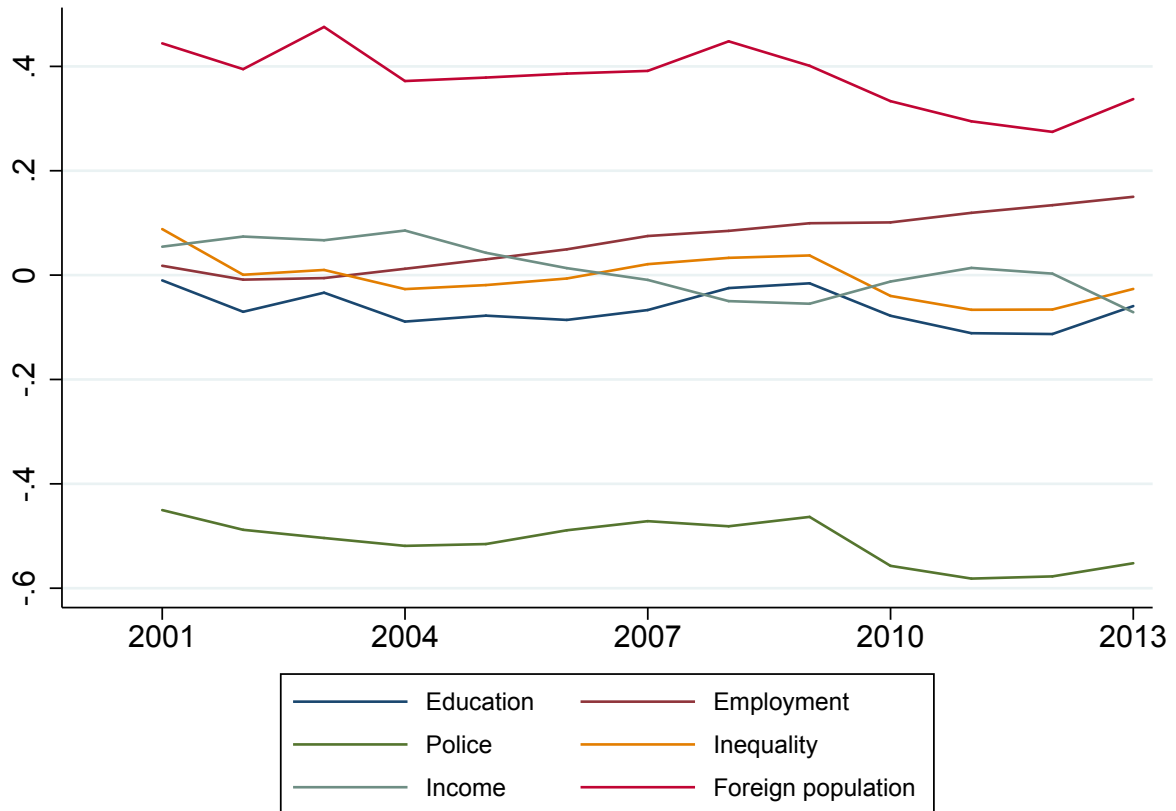
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Figure 2: Timepaths of the responsiveness scores for the period 2000–2012.

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 specifically 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 reflect different 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 affected.

4.2   Returns to scale

We move now to a deeper analysis of the phenomenon, using a particular feature enabled by the use of the responsiveness scores approach. One useful aspect is the investigation of factor accumulation returns, which produces some interesting results. As shown in Figure 3, where the responsiveness score for the first factor is plotted
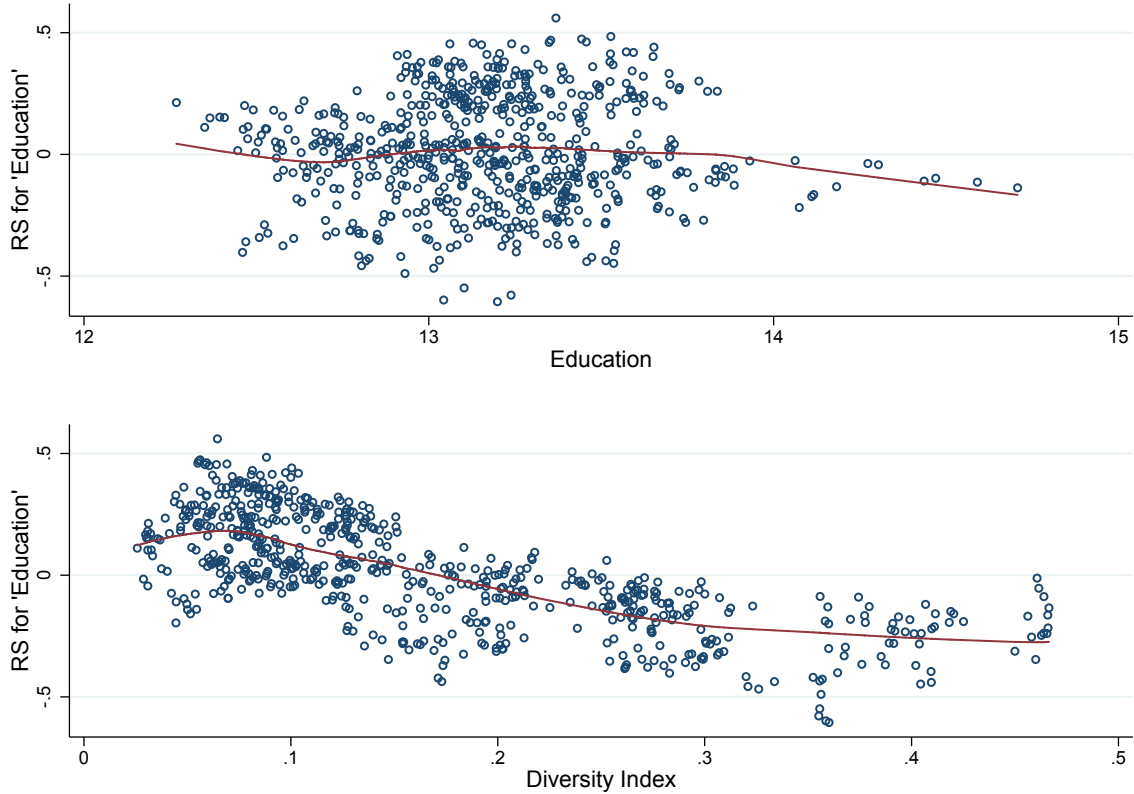

Figure 3: Factor accumulation returns for *Education*.

over the average years of schooling and the diversity index for each state, *Education* shows stable returns for the intermediate range, while decreasing at the extremes. This would suggest that an increase in the average level of education, when this is relatively low, brings a less than proportional increase in crime, while implying a decrease in the crime rate for very high levels of education. With reference to the above mentioned work by Buonanno & Leonida (2005*b*), this suggests a further non-linearity in the responsiveness to the education level. What is even more striking is the result achieved from plotting the responsiveness to *Education* and a measure of cultural diversity (Ottaviano & Peri (2006)). To investigate this, we check whether

different levels of diversity interact with the responsiveness to education. The relation is unambiguously negative, with the effect 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.
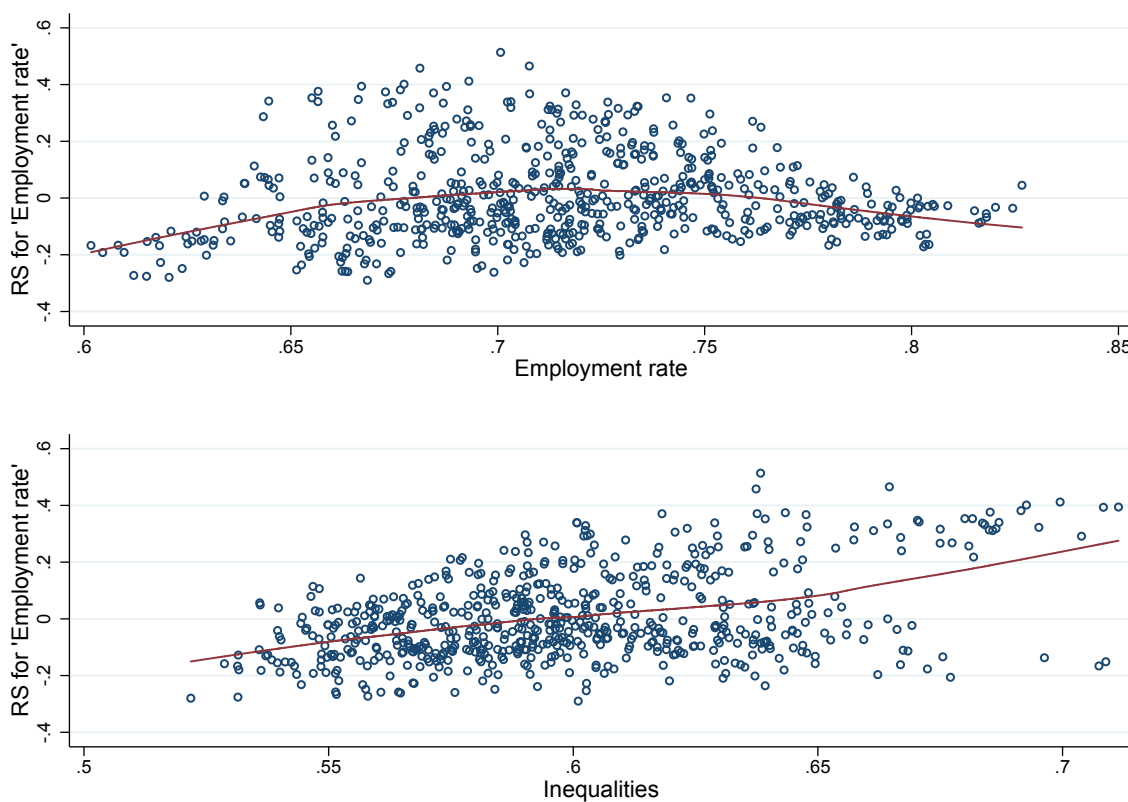
Figure 4: Factor accumulation returns for *Employment*.

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.

Therefore, the greatest effects in reducing crime rates appear to be concentrated where employment is low, and thus an increase brings a sensible change in the opportunity cost of crime, or where this is particularly high: probably high enough to dissuade criminal activity. We explore a different side of the story by plotting the responsiveness to *Employment* on the levels of income inequality, as expressed by the Gini coefficient. This time, the relation is clearly positive, implying a greater responsiveness to the employment rate with the increase of inequality. More specifically, the effect of employment on crime is negative but decreasing in absolute value for low levels of income inequality, but it becomes positive and increasing for higher values of the Gini index. When wealth is unevenly distributed within the society, even increases in employment do not benefit the poor as much as they benefit the rich, therefore triggering social tensions and incentives for criminality.

Accumulation returns of *Police* are not readily interpreted, but they nevertheless present the relevant feature of being increasing (or, in absolute value, decreasing) after a certain threshold. The first panel of Figure 5 is telling us that, although a higher presence of police has a negative impact on crime rate (as specified above, along the whole distribution), the responsiveness still suffers from decreasing returns to scale. Crime rates decrease less than proportionally with higher expenditures on police protection. Interestingly, this is not the case for the lowest level of expenditure where returns are increasing in magnitude, therefore suggesting that the presence of police is still so low that even a slight increment has a strong negative effect on crime. Overall, this seem to be a reassuring result. As pointed out by Levitt & Dubner (2005), higher expenditures on police protection can lower criminality, but if this is not paired with other complementary measures, this turns not to be necessarily the most efficient way to foster social order.

The graphs for the returns of *Inequality* and *Wage* (Figure 5) do not tell us that much: they are generally stable and flat, with the exception of a decreasing range for *Inequality* and a slight bump in the responsiveness to *Wage* for higher values.

Finally, the responsiveness score to the *Foreign born* (Figure 5) variables also shows relevant behavior. This stays very stable and close to zero when the share of foreign population stays below 20%, but it grows steeply until values of one and beyond when *Foreign born* overtakes this threshold. The fact suggests that integration is not playing a strong role in this model. Consequently, a higher percentage of immigrants tends to exacerbate crime, with changes in responsiveness that are

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.
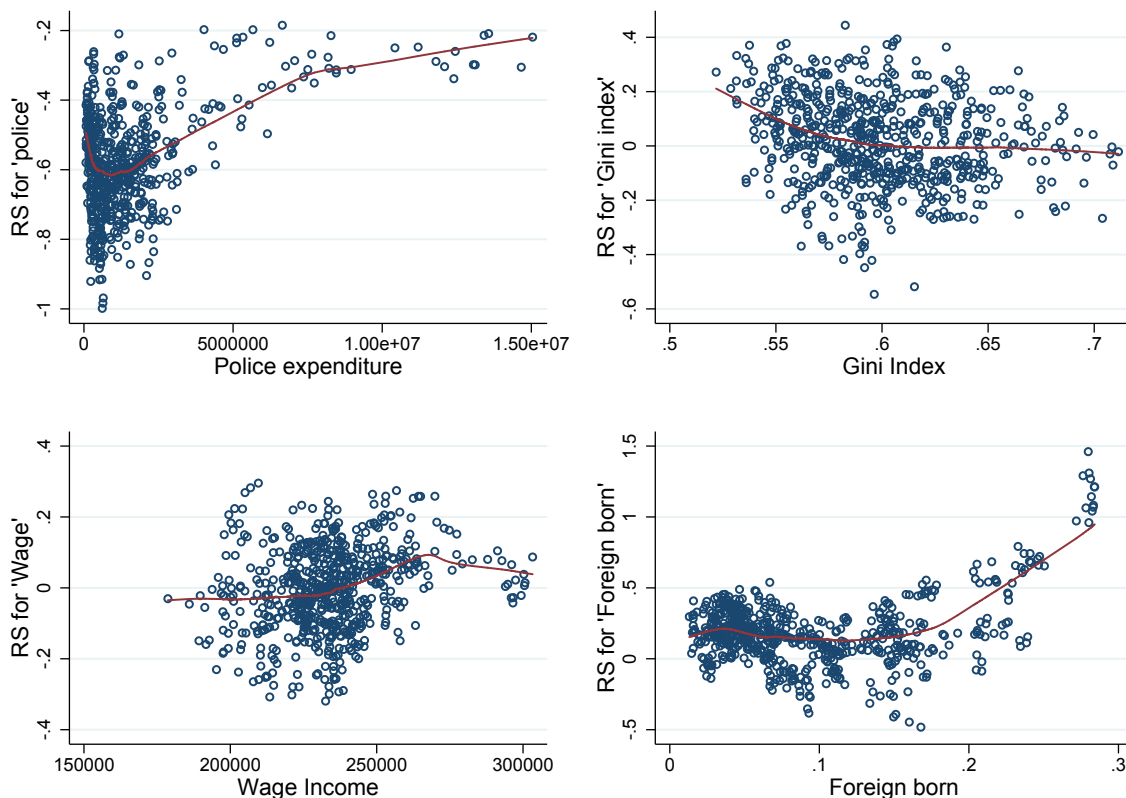

Figure 5: Factor accumulation returns for *Police*, *Wage*, *Inequality* and *Foreign born*.

4.3 Geographical patterns

Another interesting feature that we can employ by working with responsiveness scores is the possibility of using the idiosyncratic effect 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 different 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

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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
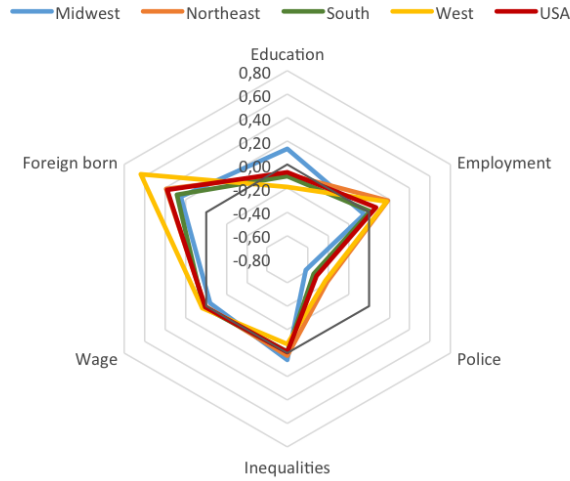
Figure 6: Incidence of factors by regions.

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 effect of additional units of the same factor.
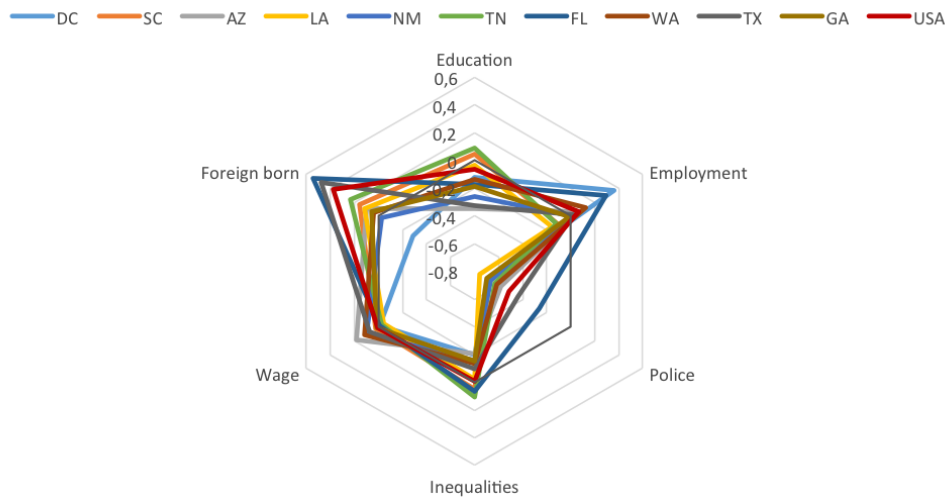

Figure 7: Incidence of factors in the highest 10 crime rate states.

4.4 Violent vs. Property crimes

We move now to testing whether our hypotheses on the existence of different effect depending on the type of crime are actually confirmed by the data. The FBI Uniform
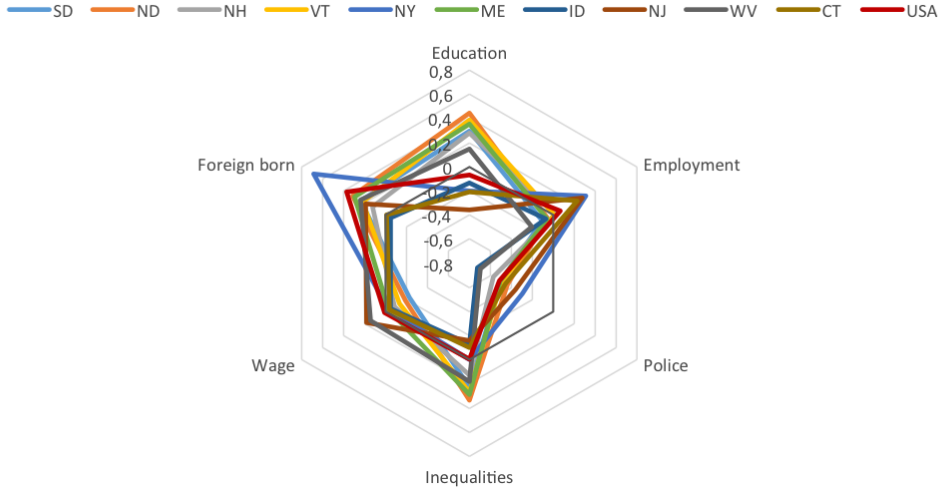
Figure 8: Incidence of factors in the lowest 10 crime rate states.

Crime Reports program (U.S. Federal Bureau of Investigation ($2010b,a$)) only distinguishes crimes according to the type of offense: *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].

We define two new variables $vcrime_{st}$ and $pcrime_{st}$, which will be our outcomes of interest in this section. They follow the same construction of the previous $crime_{st}$ such that:

$$crime_{st} = vcrime_{st} + pcrime_{st} = \frac{VC_{st}}{Pop_{st}} + \frac{PC_{st}}{Pop_{st}} \qquad (12)$$

We proceed by performing the same type of analysis with regard to the aggregate variable. The distributions of responsiveness scores look quite different for the two variables, as shown in Figure 13 in the Appendix, with the one for property crime generally much more volatile than for violent crimes. As a matter of fact, most of the factors' responsiveness scores are centered around zero for violent crimes, which can be thought as less likely to be responsive to economic conditions. On the other hand, property crime exhibits a positive correlation with education, confirming the intuition explained above for white collar crimes, as well as an inverse relation with employment.

Time trends (Figure 9) also shows peculiar paths when differentiating the two

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[8]"White collar crimes" are defined (U.S. Federal Bureau of Investigation ($2010c$)) as "those illegal acts which are characterized by deceit, concealment, or violation of trust and which are not dependent upon the application or threat of physical force or violence" and specifies that "individuals and organizations commit these acts to obtain money, property, or services; to avoid the payment or loss of money or services; or to secure personal or business advantage."

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.
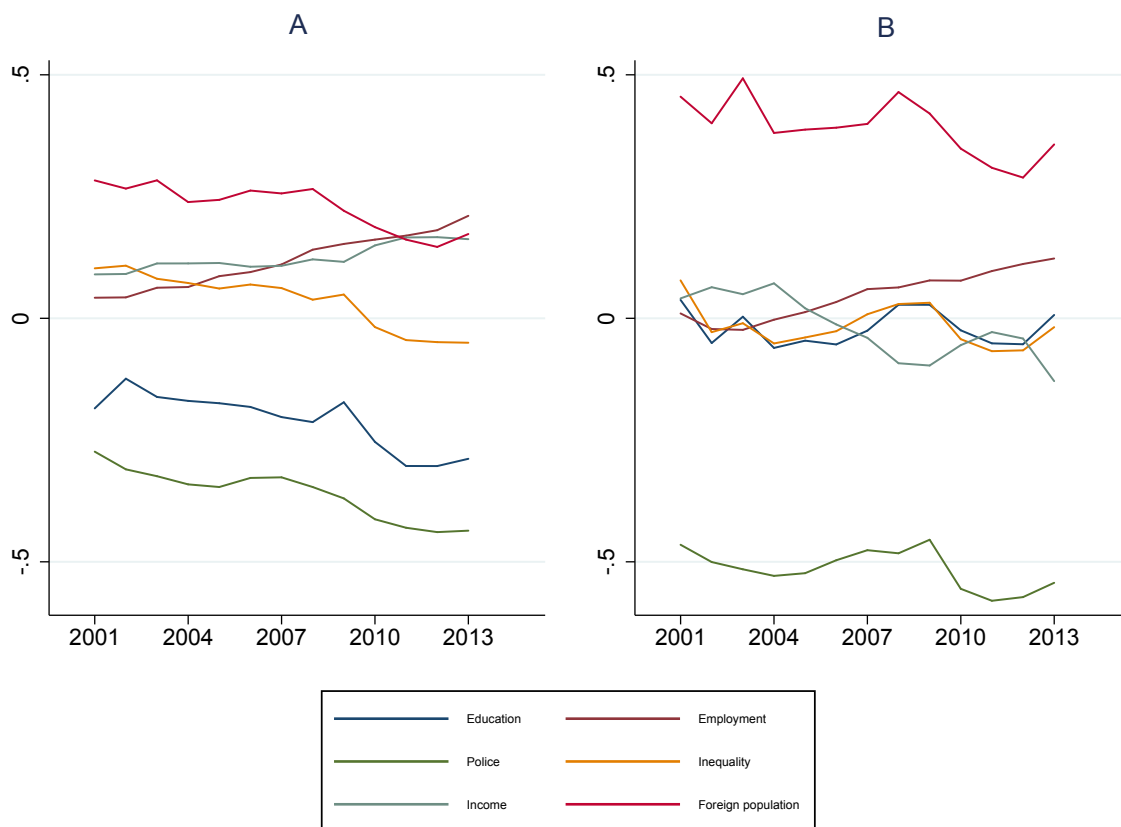

Figure 9: Time trends for (a) violent crime; (b) property crime.

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 difference. 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 effect 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.
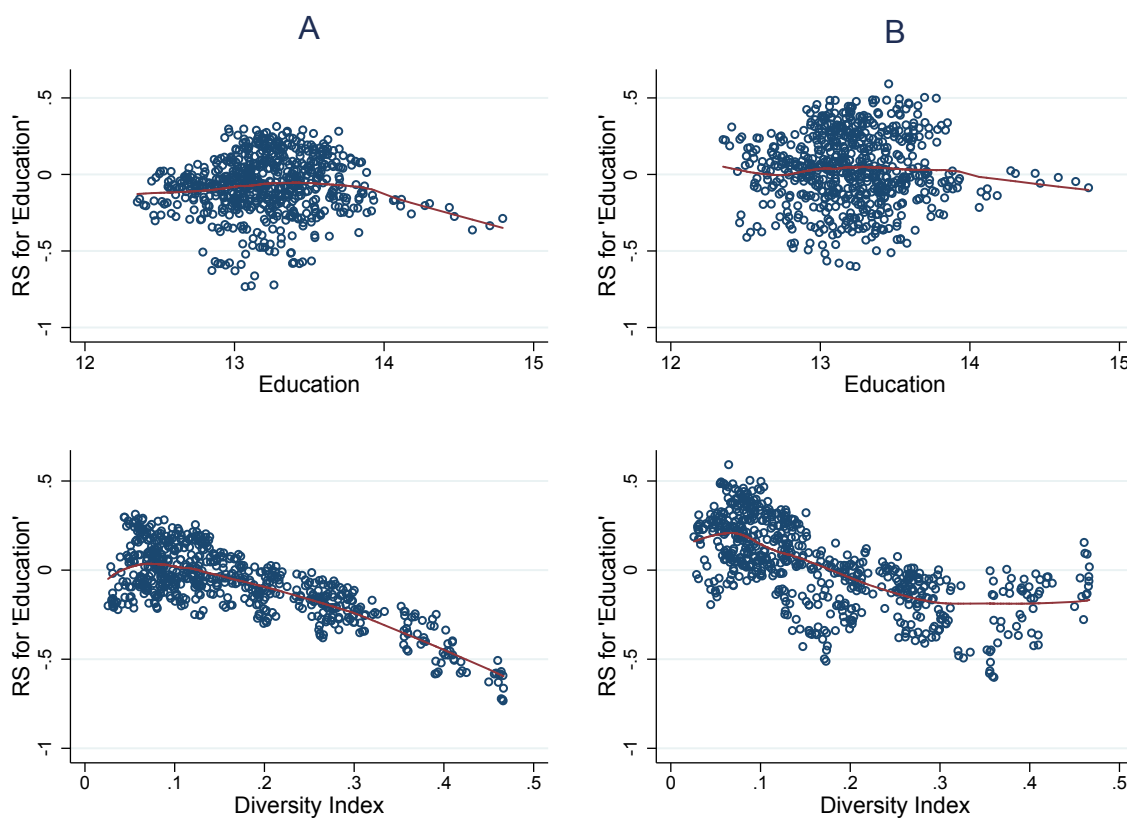

Figure 10: Factor accumulation returns for *Education*.

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

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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 is similar for property crime, although more employment reduces it for low level of inequalities, while working in the opposite direction when higher.
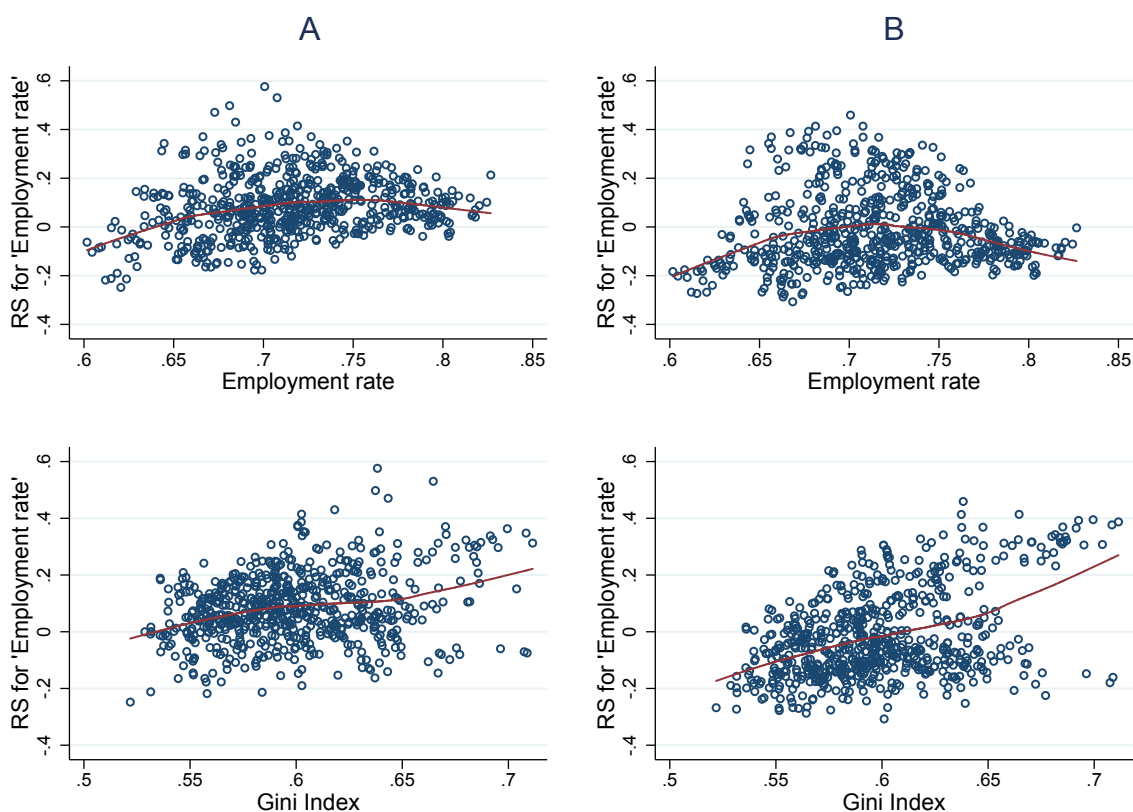

Figure 11: Factor accumulation returns for *Employment*.

In Figure 12, we also report the results for the factors *Police* and *Foreign born*. For the former, the scores are more stable in the case of violent crimes. Conversely, as some categories of property crime are less easy to detect, higher expenditures on police have returns that are decreasing in magnitude. Finally, although the presence of a larger foreign born population always exhibits positive scores, the scores are significantly higher in value, and increasing, in the case of property crime, probably

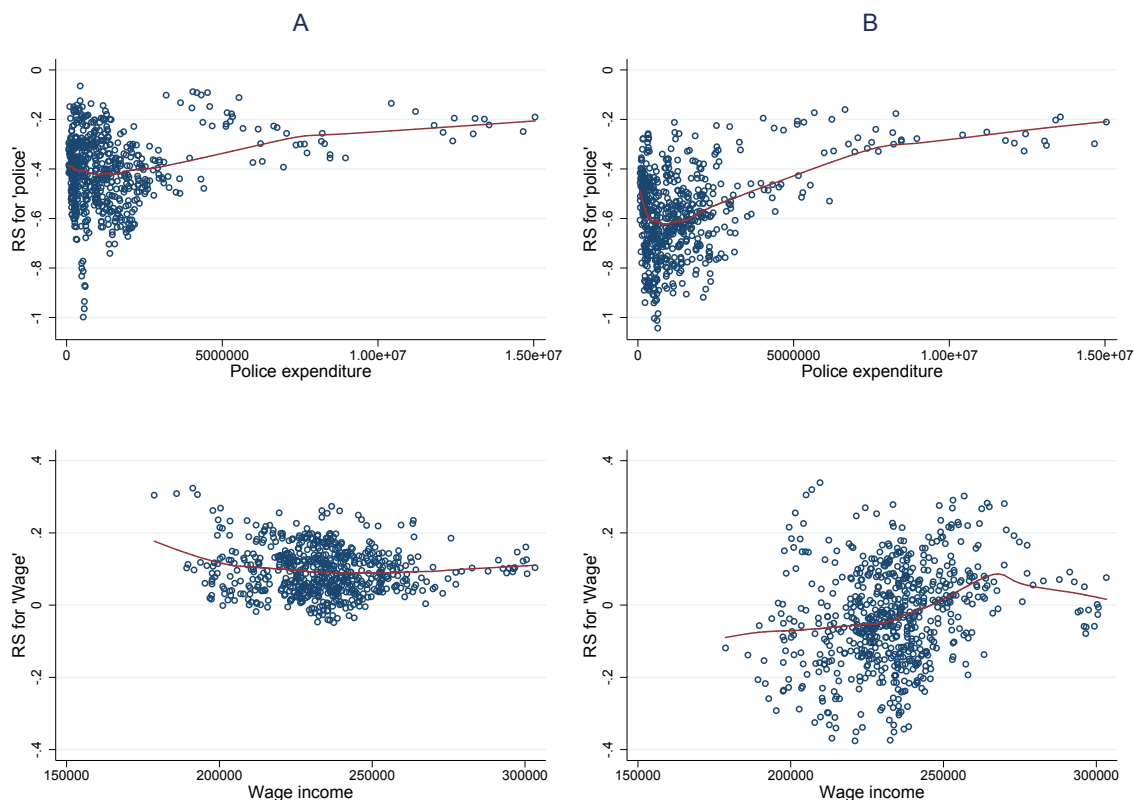signaling the less favorable economic conditions of this share of the population.

Figure 12: Factor accumulation returns for *Police* and *Foreign born*.

We report the graphs for the two residual factors, *Inequality* and *Wage* in Figure 14 of the Appendix, as they do not present relevant discrepancies from the analysis performed at the aggregate level.

5 Conclusions

This paper investigates how the level of engagement in illegal activities responds to six of the main socioeconomic factors identified in previous literature in 50 US states. The analysis of the state level idiosyncratic effects of these considered determinants is made possible by the use of responsiveness scores (Cerulli (2017)). We assess the magnitude of their effect of these six factors in each state for each year. Moreover, we have distinguished between two relevant categories of crime, and found differential behaviors in trends and factor returns for their responsiveness to the considered factors. This approach obviously presents some limitations and the numbers we have

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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 economics of crime, as our results match and provide confirmation for the findings in most of the main theories. Further works should try to verify the robustness of these outcomes, for instance through the use of different measure of the same factors, and open up the investigation to the possibility of contributions from different factors, paving the way for a greater analysis on their causal connections to crime.

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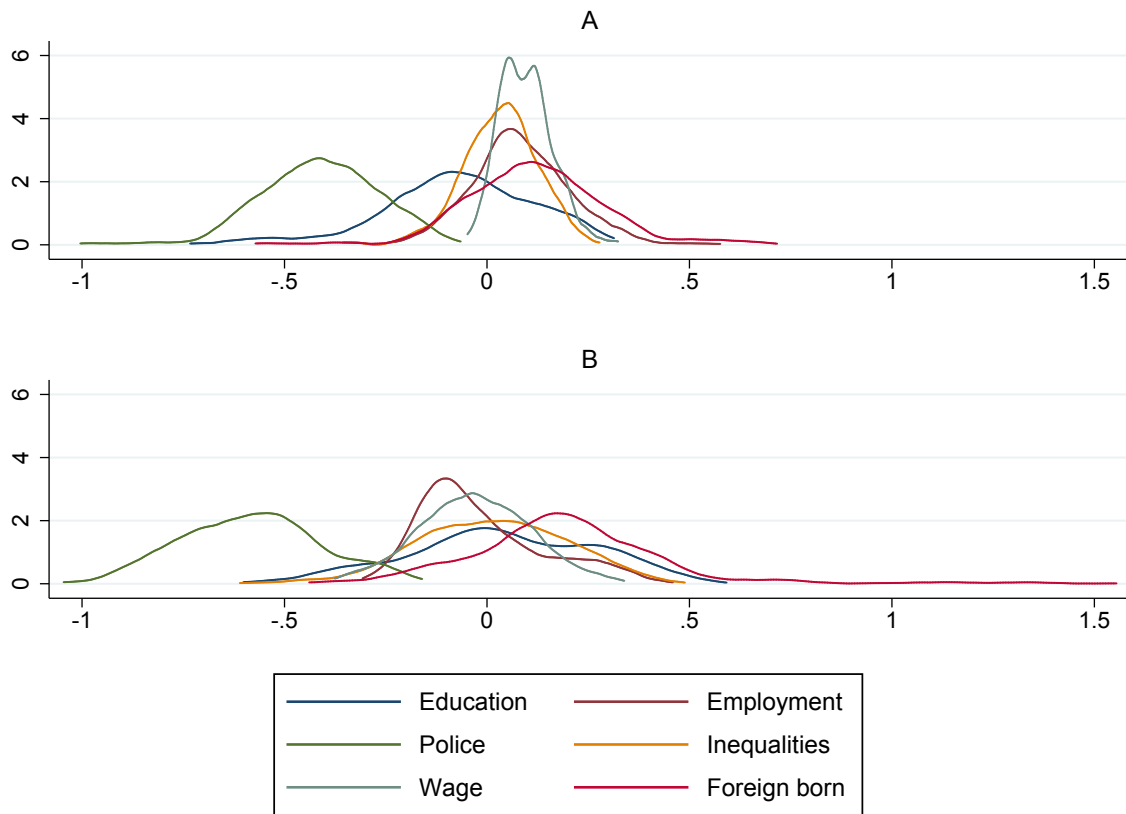
Appendix

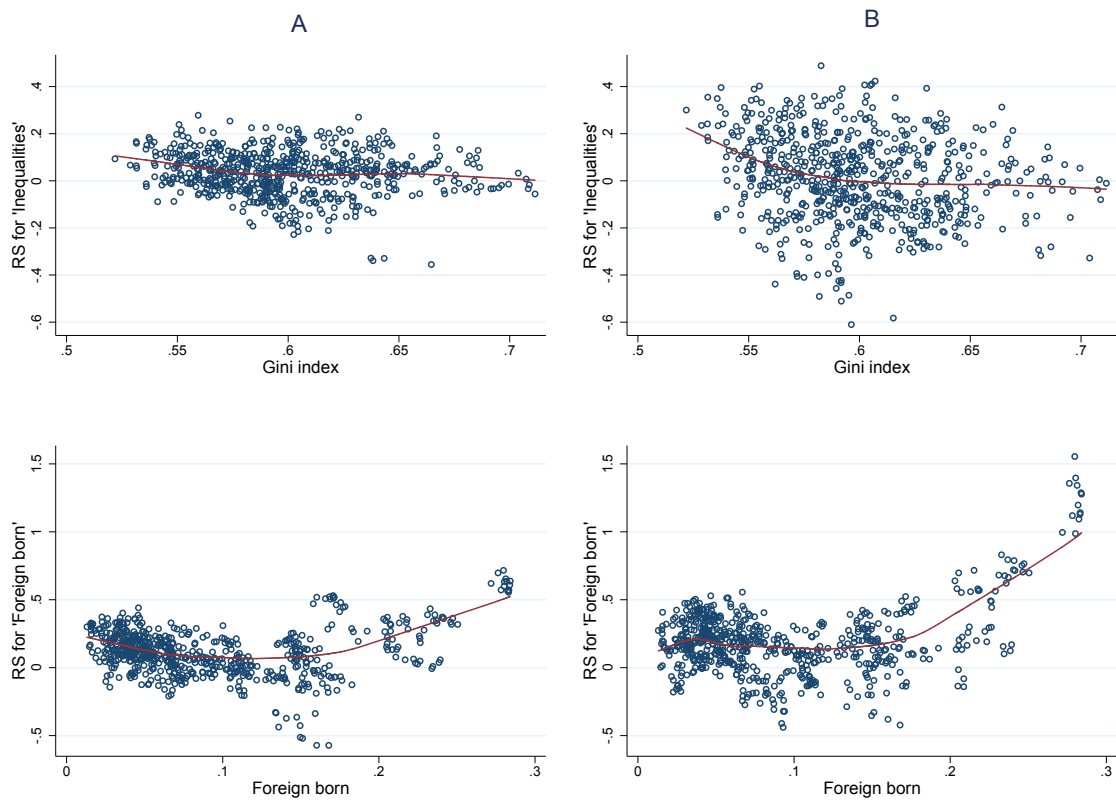Figure 13: Distribution of responsiveness scores for (a) violent crime; (b) property crime.

Figure 14: Factor accumulation returns for *Employment*.