Chapter 5
Socio-economic inequalities and Organized Crime: an empirical analysis

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1 Introduction

In this chapter we contribute to the recent literature (e.g., Istat, 2010, Acciari et al., 2016, Guell et al., 2017) that provides evidence that inequality is high and social mobility is low in the Italian regions and provinces where organized crime is widespread such as those of Southern Italy. We complement this line of work in two respects. First, using a novel panel dataset at the regional level for the period 1985-2014 we investigate the relationship between inequality and organized crime at the regional level, exploiting both time and cross-sectional variation.[6] Second, we assess the role of social mobility in organized crime.

Our main hypothesis is that both inequality and intergenerational persistence lead to organized crime. There exist various mechanisms for why income inequality matters. In particular, *direct* channels may be at work, for example if poor individuals find organized crime attractive for lack of remunerative alternatives in the labor market. Alternatively, rich individuals, for example members of the economic and political *élite*, may demand organized crime ``services" to gain or preserve their socio-economic standing. Franchetti (1877) initially pointed out this behavior in his thorough enquiry on Sicily at the time of reunification of Italy, as he noted that the Sicilian upper class benefited from the protection services by

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[6] Some previous work has studied the relationship between inequality and corruption (e.g., Jong-Sung and Khagram, 2005), violent crime (e.g. Fajnzylber, 2005) and civil conflict (e.g., Macours, 2010).

the early *mafiosi*. Recent evidence supporting this claim is found for example in Gambetta and Reuter (1995), describing how entrepreneurs can gain monopolistic power by forming cartels enforced by criminal organizations in the adjudication of public contracts,[7] and by De Feo and De Luca (2017), who provide evidence on the support that Mafia can give to local politicians in exchange for economic benefits. In addition, *indirect* channels can also be at work. This occurs if the expected returns from organized crime, including possible punishment and opportunity costs, are higher than the expected return of the individuals' legal alternatives. Our conjecture is that there might be more gains from involvement in organized crime in the presence of inequality as the latter is likely to lead to corruption and erosion of the rule of law (Jong-Sung and Khagram, 2005; Sunde et al., 2008).

In addition, we expect that low socio-economic mobility favors organized crime development. This fact, as noted, is suggested by the empirical analyses of Acciari et al. (2016), and Guell et al. (2017), although in these articles this issue is not considered. Our hypothesis is motivated by the ideas of memberships theory of inequality put forward by Durlauf (1996, 1999, 2006). Cross-sectional inequality leads to segregation that generates gaps in the life-time outcomes of children that in turn generate intergenerational immobility. Durlauf shows how the co-existence of social interactions and residential segregation can lead to intergenerational persistence. The idea is that in the presence of complementarity, parents (e.g., role models) will make choices about the locations where their children grow up to affect their social environment. This leads to neighborhood stratification by income and incentives for segregation. Segregation in turn creates great gaps in the capabilities and outcomes of children as they grow up to become adults. The higher the degree of segregation, the larger are the gaps in human capital between children from rich and poor neighborhoods. This creates the Great Gatsby Curve (Durlauf and Seshadri, 2018). More precisely, assuming local public finance of education, rich families will sort themselves into rich and low-crime neighborhoods with high-quality schools and services. Poor families will sort themselves into high-crime neighborhoods with poor schools and services. This implies that a child who grows up in a disadvantaged neighborhood will receive poor education and it more likely to be exposed to a host of negative social interaction effects such as the lack of exemplar role models and negative peer effects that can influence educational and health outcomes or lead to delinquent behavior.

[7] See also Gambetta (1993) for an analysis of the Sicilian Mafia as a provider of private protection and Lavezzi (2014) for a discussion of the concept of "demand for Mafia".

In contrast, favorite outcomes are expected for the human capital and skill formation of the children raised in rich neighborhoods. These gaps are then transmitted from generation to generation giving rise to intergenerational persistence.

Our hypothesis is that in such neighborhoods *Mafiosi* can represent relevant role models, so that members of young generations have an incentive to fill the ranks of criminal organizations. On the other hand, rich families tend to cluster to exploit positive spillovers from other rich families. In connection with the argument we made to motivate our hypothesis on the relationship between inequality and development of organized crime, we argue that in dynamic setting, offspring of rich families can have an incentive to exploit the same channels that members of previous generations had to increase income and accumulate wealth, including the utilization of the services provided by organized crime. Although our interest is on the causal link going from social mobility to organized crime development, important feedback mechanisms can be at work, so that at this stage we cannot make strong claims of causality and just look for robust correlations between measures of socio-economic mobility and of organized crime.[8]

Indeed, the few existing works investigating the relationship between organized crime and social mobility study the causal link going from the former to the latter. Coniglio et al. (2010) and Caglayan et al. (2017) in particular show that the presence of organized crime within the territory interferes with human capital accumulation. In particular, Coniglio et al. (2010) argue that the presence of organized crime in Southern Italy, especially in the region of Calabria, hinders human capital accumulation by reducing incentives to invest in education and by increasing migration outflows. Caglayan et al. (2017) instead provides empirical evidence of less accumulation of human capital in provinces of Northern Italy where the presence of organized crime is widespread.[9]

[8] Work is in progress to analyze this issue in the city of Palermo.

[9] Other works investigate the effect of other types of crime on social mobility. For example, Savolainen et al. (2015), using birth cohort data from Finland, examine the relationship between intergenerational educational mobility and criminal activity noting that rates of criminal offending is strongly related to family background. Differently, Sharkey and Torrats-Espinosa (2017), using longitudinal data on US, find evidence that a decline on violent crime in a county increases the upward economic mobility in adults who had experienced this drop during the late adolescence. Moreover, they show that a decline in the violent crime rate reduces the high school dropouts at the county level.

In our empirical analysis we construct different measures of organized crime, which are based on Calderoni (2011) and on dynamic factor methods (Moench et al. 2011, Banbura and Modugno 2014). Furthermore, we use different inequality indices. Our main finding is that higher inequality leads to higher organized crime development. The results are robust for different organized crime measures and inequality indices. For all measures the ratio of 90^{th} quintile over the 10^{th} in the distribution is a strong predictor of organized crime, even if we control for other covariates that capture economic development, education, etc. We also find that consumption inequality performs better that income inequality as the relevant inequality measure. Finally, we conduct a provincial level analysis to study the effect of socio-economic mobility on organized crime, using the Calderoni-based indices. We consider three alternative measures of social mobility. We find that lower socio-economic mobility displays a robust association with organized crime development.

This chapter is organized as follows. Section 2 contains the description of the dataset; Section 3 describes the methodology employed for the empirical analysis; Section 4 presents the results; Section 5 contains a discussion of our results; Section 6 contains some concluding remarks.

2 Data

Our dataset on organized crime and inequality takes the form of an unbalanced 5-year period panel for 20 Italian regions for the period 1985-2014. A detailed description of the data and our sources is given in the Data Appendix Table A1. While we construct the organized crime variables (OC) at the annual frequency we opt to use 5-period averages to reduce measurement error bias and ease the problem of missing observations in several explanatory variables.

Data on income inequality are obtained from the Survey on Household Income and Wealth (SHIW) provided by Bank of Italy, which comprises about 8,000 households (20,000 individuals) per wave. This survey includes information on personal income, household consumption and wealth, education and occupation. Data on socio-economic mobility are from Acciari et al. (2017), and come from Italian tax data at provincial level.

2.1 Measure of organized crime

To measure organized crime, we follow the current literature and utilize data on crimes committed by members of criminal organizations. Data on crimes come from Istat and the SDI database, managed by the Italian Ministry of Interiors.[10] Our analysis distinguishes between two types of crimes measures. Type I includes direct measures, i.e. crimes that unambiguously are related to organized crime (2 crimes): Homicide by Mafia and Mafia Type Association. Type II includes indirect measures, i.e. crimes that are potentially associated to organized crime (14 crimes): Criminal Association, Bribery, Corruption for an Act Against Official Duties, Drugs, Extortion, Money Laundering, Prostitution, Smuggling, Threats, Usury, Corruption in Public Acts, Instigation to Corrupt, Judicial Corruption, Kidnapping for Extortion Purposes.[11]

Our organized crime measures are based on the joint consideration of type I and II crimes. We choose to measure organized crime in this way as the relevance of crimes of Type II is remarked in several reports on the activities of Italian mafias (see, e.g. Dia, 2016), as well as in the literature (see, e.g. Riccardi et al., 2016, and Fioroni et al., 2017). This approach distinguishes us from, e.g., Calderoni (2011) who focuses on type I crimes only.[12] In addition, from a statistical point of view, we see organized crime as a latent variable, measured with error. In this perspective, the higher the number of crimes we consider to measure organized crime, the lower the measurement error.

Our organized crime variables are based on two alternative approaches using 16 crime variables. The first one is based on Calderoni (2011) and the second approach employs novel dynamic factor methods proposed by Moench, Ng, and Potter (2011) and Banbura and Modugno (2014).

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[10] We are grateful to Magg. Domenico Martinelli and to Claudia Di Persio for invaluable help, and to the Department on "Analisi Criminale della Direzione Centrale della Polizia Criminale" at the Italian Ministry of Interiors for releasing the data.

[11] In our empirical analysis, crime numbers are normalized by population.

[12] Crime data in Calderoni (2011) are integrated by data on other direct measures of Mafia activities: the number of city councils dissolved for Mafia infiltration, and a measure of assets confiscated to Mafia clans. See the same article for details on other methods to measure organized crime found in the literature.

Following Calderoni (2011), we employ two alternative procedures to calculate the Mafia Index. In the first one, we first normalize each variable to take values between 0 and 100 with 100 to denote the highest value of Mafia presence. Then, we compute the *Calderoni Mean Index* as the average score of all variables. One problem with the average score is that may overestimate the presence of the mafia in the Southern regions and underestimate it in the other regions. This is because organized crime is prevalent in the areas of southern Italy. To overcome this problem we also construct an index based on region's rank. For each variable, we rank all the Italian regions in decreasing order. Then we attribute the score of 100 to the region with the highest rank and proportionally lower scores to the other provinces, according to their rank. Then, we compute the *Calderoni Rank Index* as the average score of all variables (see Table 1 in the online appendix for summary statistics).

We employ the dynamic factor model method to extract a latent factor for organized crime at the regional level. This methodology has not been applied to such a purpose before. Let $x_t = (x_{1t}, x_{2t}, \dots, x_{nt})', t = 1, \dots, T$ denote a stationary n-dimensional vector of crime series standardized to mean 0 and unit variance. We assume that the factor model takes the following form:

$$\mathbf{x_t} = \mathbf{\Lambda f_t} + \mathbf{e_t} \qquad (1)$$
$$\mathbf{f_t} = \mathbf{A f_{t-1}} + \boldsymbol{\eta}_\mathbf{t} \qquad (2)$$

where f_t is a $r\times1$ vector of latent common factors of organized crime and $e_t = (e_{1t}, e_{2t}, \dots, e_{nt})'$, is the idiosyncratic component, uncorrelated with f_t at all leads and lags[13]. The errors η_t are assumed to be innovations to the factor. The common component is given by $n\times r$ matrix Λ, which contains factor loadings.

Following Banbura and Modugno (2014) we estimate the dynamic factor model using a modified Expectation Maximisation (EM) algorithm. The idea of the algorithm is to write the likelihood as if the data were complete and to iterate between two steps: in the Expectation step the missing data are filled in the likelihood, while in the Maximisation step this expectation is re-optimised. This modification is important in our

[13] The errors were not allowed to be serially correlated, but this assumption can be relaxed later.

analysis as it allows us to consider a larger number of time-series that organized crime regardless of whether they have missing observations or not.

In addition to the latent factor at the regional level we extract factors at the macro and Italy level for descriptive purposes. In doing so, we employ two complementary factor analyses. First, we apply the aforementioned methodology separately at different levels of aggregation. Figures 1 (in the online appendix) and 2 provide the t-plots of the factors for results for Italy-wide and the macro area factors (Centre, North and South), respectively. It can be observed that there are some large spikes at the beginning of the period, indicating a higher intensity of the phenomenon, while fluctuations are much smaller in the subsequent years.

Table 2 presents the estimated the loadings of the factors and Table 3 the square loadings (as % of total) to illustrate the relative importance of the different crimes[14]. Table 3 suggests that some of the indirect measures of organized crime may have a high capacity to capture the phenomenon, and that the effect is different across the different Italian macro regions. For example, different corruption crimes stand out (see, e.g. Fioroni et al. 2017, on corruption and organized crime), as well as money laundering in the South (see Barone and Masciandaro, 2011, for an analysis of organized crime and money laundering).

Second, we employ the hierarchical dynamic factor models proposed by Moench, Ng, and Potter (2011) to account for the correlations between the shocks at the different levels of aggregation. In particular, we employ this multilevel factor model using common (Italy level - global), block-specific (macro regions), and sub-block-specific (regions) to capture the within and between-block variations in the measurement system of organized crime. Given that this method does not allow for missing observations, we only use a set of five variables (Criminal Association, Drugs, Mafia type Association, Extortions and Prostitution). As it is illustrated by Figures 3 (in the online appendix) and 4, the common factor exhibits a similar pattern to the one we obtained using the first method in Figures 1 and 2 although it is only based on a much smaller set of variables. Table 4 presents the variance decomposition analysis to document the examine the importance of the variation of aggregate (Italy-wide), block-specific (Mac-

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[14] The factor loadings (estimated as stationary, non time-varying, values) can be interpreted as weights telling how much the factor intensity depends (loads) on each crime over the period of interest.

ro), and subblock-specific (Regional) components as well as idiosyncratic noise (IdioNoise) relative to the total variation in the data.

The variations due to idiosyncratic shocks dominate other variations, in all cases. Overall, we can see that regarding the other variations, the subblock specific variations are larger. Notice in particular that in Southern regions (where organized crime is more widespread), the regional component is relatively high.

2.2 Inequality and socio-economic mobility

We employ six different inequality metrics that capture different aspects of the distribution: (i) the Gini index, (ii) the Atkinson inequality index[15] - and four percentile ratios - (iii) P90/P10, (iv) P75/P25, (v) P90/P50, and (vi) P75/P50. The Gini and Atkinson indices take value between 0 and 1 as opposed to the percentile ratios that do not have this restriction. For each inequality metric, we construct 2 different measures of inequality based on total consumption and net income. For inequality measures on consumption and household income, we consider all the observations in which the heads of household are aged from 25 to 65. Table 5 in the online appendix presents summary statistics of these inequality measures.

For socio-economic mobility, we use the measure computed by Acciari et al. (2016), based on Italian tax data. In particular our measures of mobility measure immobility between parents' income in 1998 and children's income in 2012 at provincial level. The three indices we consider are: i) *Relative mobility*: this is the slope of a rank-rank regression between child ranks and parent ranks and measure the difference in outcomes between children from top vs. bottom income families within province (Chetty et al., 2015). A high value indicates low mobility; ii) *Absolute mobility – expected rank*: this index measures the expected rank of children from families at the bottom 25% of the national parent income distribution (Chetty et al., 2015). A high value indicates high mobility; iii) *Absolute mobility – Q1toQ5* measures the probability of rising from the bottom quintile to the top quintile of the income distribution (Corak and Heisz 1999, Hertz 2006). A high value indicates high mobility.

[15] For definitions and details on the Gini and Atkinson index see e.g. Cowell (2011).

2.3 Other covariates

We considered as covariates in our analysis indicators of the economic conditions and of human capital, under the assumption that bad economic conditions and low levels of human capital can positively affect organized crime development. In particular, we used secondary education level, the economic activity rate, the growth rate of compensation of employee, the growth rate of total hours worked, the participation in education and training, the long-term unemployment rate, the growth rate of gross fixed capital formation (see Table A1 and Table 6 in the online appendix for the definitions and for summary statistics).

3 Methodology

The focus of this paper is to investigate how changes in organized crime (OC) are related to inequality (INEQ).

Our benchmark model takes form of a dynamic panel model:

$$\boldsymbol{OC_{it}} = \boldsymbol{\rho OC_{it-1}} + \boldsymbol{\beta_I INEQ_{it}} + +\boldsymbol{\gamma' Z_{i\square}} + \boldsymbol{\xi_t} + \boldsymbol{v_i} + \boldsymbol{u_{it}}, \qquad (3)$$

where v_i is the fixed effect, ξ_t is the time effect, and u_{it} is the idiosyncratic error term. Z_{it} includes a constant and other covariates. Following Blundell and Bond (1998), we estimate this model using system 2-step GMM up to 4 lags as instrumental variables and robust standard errors[16]. Given that the impact of inequality on organized crime development can be not contemporaneous, we also tried specifications with a lagged value of INEQ.

In the case of measurement of organized crime by the estimated dynamic factor, we had to consider differences in this variable to make the series stationary. This implied considering also INEQ in differences. In this case the estimated dynamic panel takes the form:

$$\boldsymbol{\Delta OC_{it}} = \boldsymbol{\rho \Delta OC_{it-1}} + \boldsymbol{\beta_I \Delta INEQ_{it}} + \boldsymbol{\gamma' \Delta Z_{it}} + \boldsymbol{\xi_t} + \boldsymbol{v_i} + \boldsymbol{u_{it}} \qquad (4)$$

[16] We implement this estimation using the Stata package xtabond2 by Roodman (2009).

As for socio-economic mobility, given that our data are only available as a cross-section we estimate a simple cross-sectional regression of the form:

$$\boldsymbol{OC_i = \beta_I INEQ_i + \beta_M SM_i + \gamma' Z_i + u_i} \qquad (5)$$

The next section contains the results of our econometric analysis.

4 Results

This section presents the results of our econometric analysis. In particular, Section 4.1 discusses the results on inequality and organized crime, while Section 4.2 those on socio-economic mobility and OC.

4.1 Organized Crime and Inequality

Tables 7 and 8 contain the results of regressions of organized crime on INEQ for both indices based on Calderoni (2011), i.e. *Calderoni Rank Index* and *Calderoni Mean Index*, considering respectively indices of income inequality and consumption inequality[17]. The results show that the coefficients of the effect of inequality on organized crime have positive and significant coefficients in particular when the *Calderoni Mean Index* is utilized in the regressions. Moreover, it appears that consumption inequality better captures the relationship of interest. The inequality index with the highest level of significance is P90/P10. Under the null of joint validity of instruments, the Hansen's test of over-identification provides us enough evidence about the validity of our instruments, in all models (at least at 5% significance level).

Table 9 contains the results of specifications in which we added lagged values of inequality indices.[18] Results in Table 9 shows that, with the *Calderoni Mean Index*, all six metrics of inequality measures have positive and significant coefficients: in particular, the contemporaneous values of P90/P10, P90/P50 and P75/P50 and the lagged values of the Gini and

[17] Regressions are run on data from 19 out of 20 Italian regions. The region of Val d'Aosta is dropped for lack of data.

[18] We only report the results for consumption inequality. Results for income inequality return a significant coefficient only with the *Calderoni Mean Index* for the lagged values of the Atkinson index (at 5%) and of P90/P10 (at 1%).

X 25/1/y 15:33

Commenta [1]: Can you discuss this claim? Why are the results better for consumption inequality? I think this is important as in the rest you focus on consumption inequality vs income inequality
THIS WILL BE DISCUSSED IN THE NEW SECTION 5

X 2/11/y 13:37

Commenta [2]: This is not what I see from tables 7 & 8. The different measures of inequality perform quite differently. The only measure always significant and positive in both tables is P75/P50. Can you check and eventually provide a bit more discussion?

Mario Lavezzi 25/1/y 17:38

Commenta [3]: The comment by the editor makes some sense. Considering Tables 7 and 8, P90/P10 is significant 3 times out of 4, P75/P50 is significant 4/4. The choice of P90/P10 as our preferred measure is dictated by the fact that it is the only one significant at 1% two times. Do we stick to this justification? Alternatively, we can make this choice after showing the results in Table 9, and say that P90/P10 is the only that, after estimating a model with lagged values of inequality indices, is significant 2 times out of 4 (i.e. in its contemporaneous value with Calderoni Mean Index and lagged value with Calderoni Rank) with consumption ineq. and in its lagged value with Calderoni Mean Index. Or there is another explanation? For example in the regressions with lagged values of inequality indices and covariates, P90/P10 performs better than other measures

Atkinson Indices and P75/P25. In the case of the *Calderoni Rank Index*, the coefficients of the lagged values of the Atkinson index, P90/P10, P75/P25, P90/P50 are positive and significant.
Table 10 contains the results of regressions in which we added other covariates, related to potential economic determinants of OC.[19] Given the results presented in the previous tables we kept as our preferred metric of inequality the P90/P10 index and its lagged value. Table 10 shows that the lagged value of P90/P10 has a positive and significant coefficient in almost all the specifications with the Mafia Rank Index.

X 2/11/y 13:39
Commenta [4]: This choice does not seem coherent with what is shown in the previous tables. Please check

Table 11 presents the results where the measure of organized crime is based on the innovative method we described in Section 2.1.2, based on the estimation of a dynamic common factor.[20] We can see that the coefficients of the indices of inequality (in this case appearing as differences) have positive and significant coefficients with the exception of P75/P25 and P75/P50.

Table 12 (in the online appendix) contains the results of the regressions with additional covariates when we consider the effect of consumption inequality on the factor index computed following Banbura and Modugno (2014). [21] We can observe that in almost all the specifications the effect of inequality (in differences) is positive and significant.

4.2 Organized Crime and Socio-economic Mobility

X 25/1/y 16:24
Commenta [5]: This part is also interesting and provides results which look a bit more robust (all measures of mobility have the expected sign and are significant). Would it be useful to provide a bit more discussion going beyond the presentation of the results? The whole section is made of just one paragraph… THIS WILL BE DISCUSSED IN THE NEW SECTION 5

In this section, we present the results of cross-section regressions estimating the effect of indicators of socio-economic mobility on OC. The analysis is carried out at provincial level. Table 13 in the online appendix contains the summary statistics. Table 14 contains simple regressions of our two organized crime measures (Calderoni Rank Index and Calderoni Mean Index) on the three metrics of socio-economic mobility we considered in this report only and a constant, while Tables 15, 16 and 17 (in the online appendix) adds the covariates related to economic conditions and

[19] We only report results for consumption inequality. Regressions on income inequality returned positive and significant coefficients for the lagged value of P90/P10 in Models 1,2,4,5 with the *Calderoni Rank Index*.

[20] We only report results for consumption inequality, as regressions on income inequality measures did not return significant results.

[21] We also estimated regressions using the Hierarchical dynamic factors, but the results were not significant. This is likely due to the fact that we used only five variables to estimate them.

human capital levels to regressions with the *Calderoni Mean Index*[22]. The mobility indices' coefficients have the expected signs and are highly significant. The same result holds for Table 18 (in the online appendix), which reports the results for the correlation of the relative mobility index on the *Calderoni Rank Index*[23].

5 Discussion

The main findings of our study are twofold. First, it documents the linkages between organized crime and inequality. We find that higher levels of inequality can lead to higher organized crime development using the percentile ratio P90/P10 of consumption inequality. Second, we find that lower levels of socio-economic mobility are associated with organized crime development.

An important issue is whether changes in welfare are better measured by consumption inequality rather than income inequality, especially when one examines the role of inequality in organized crime. As argued by Attanasio and Pistaferri (2016) consumption inequality is potentially a better measure of changes in welfare than income inequality. According to Friedman's permanent income hypothesis households prefer a smooth consumption flow, that is, they choose to consume a constant fraction of the permanent income because annual income is too volatile. Assuming that income can be decomposed into a permanent component and a transitory component (e.g., MaCurdy (1982)) we would expect permanent shocks (e.g., a technological shock that affects the need for unskilled workers) to affect consumption and welfare because it harder to insure against them. In contrast, we would not expect transitory shocks to affect consumption because individuals can smooth those shocks by borrowing or using their assets. In practice, however, full smoothing is infeasible due to the presence of borrowing constraints and other imperfections of credit and insurance markets. For these reasons, we consider both consumption and income inequality when we study their role in organized crime. Interestingly, we find that consumption inequality much greater impact on organized crime than income inequality.

[22] The set of covariates used for the regional and provincial analysis do not perfectly match because of data availability. Model 7 in Tables 15, 16 and 17 contains a dummy for the Northern regions as the latter proved to be highly significant in regressions on the mobility indices and macro-region dummies.

[23] The results for the other mobility indices are not significant.

These results shed new light on the economic explanations of the rise and spread of organized crime and suggest potential policy interventions. For example, the fact that consumption inequality seems to matter more than income inequality, suggests that what matters are differences in actual standards of living, which are better captured by consumption levels than by income levels as they depend on life-cycle decisions (see e.g. Jappelli and Pistaferri, 2010, for recent trends of income and consumption inequality in Italy). This directly points out a policy response in terms of insuring adequate standard of living to the poor in order to reduce the existing disparities. The same holds for improving the socio-economic mobility, especially by improving the perspective of those lagging behind the social ladder.

6 Conclusions

This study investigates the linkages between organized crime and inequality and social mobility. In doing so we construct a novel dataset of organized crime at the regional level based on two complementary approaches. The first one is based on the methodology developed by Calderoni (2011) and the second one employs a dynamic factor model. Additionally, we construct a wide range inequality as well as social mobility measures. Our dataset is of general interest beyond the specific application considered in the present study. Our main finding is that higher inequality can lead to higher organized crime development: in particular, the index that better captures the effect of inequality is P90/P10. We also find that consumption inequality performs better that income inequality as the relevant inequality measure. Finally, we find that low socio-economic mobility displays a robust association with organized crime development.

Figures

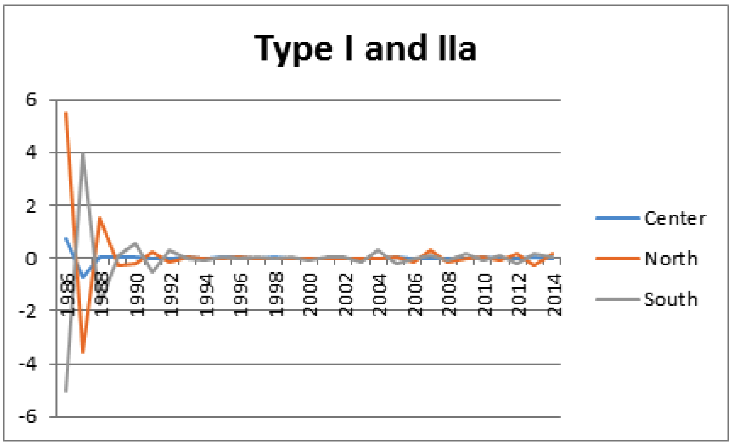

Figure 2: Factor for Organized crime based on Banbura and Modugno (2014) - Center, North, South Factor levels

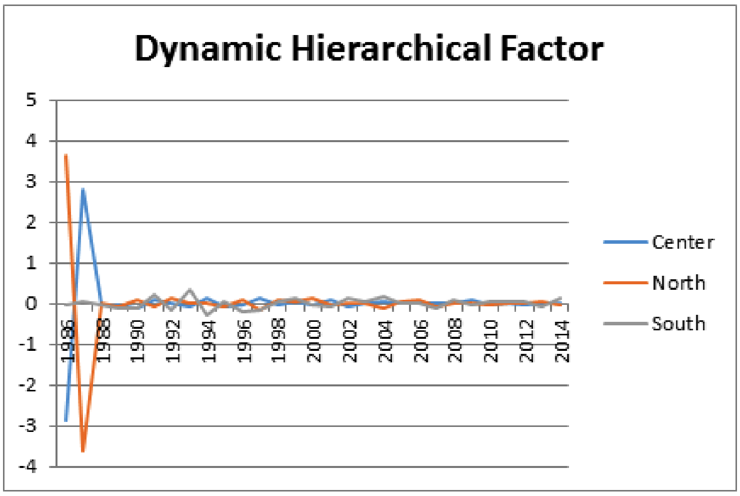

Figure 4: Factor for Organized crime based on Moench, Ng, and Potter (2011) – Macro Regions

Tables

	Italy	North	Center	South
Bribery	-3,966	4,294	-31,185	-0,257
Corruption for an action against official duties	-0,007	-3,089	-7,915	-4,077
Criminal association	0,765	-0,406	-3,635	0,510
Drugs	0,032	-0,007	-0,942	0,019
Extortions	0,242	-0,098	-0,516	0,219
Homicide by Mafia	-0,168	-0,146	-0,732	-0,163
Mafia type Association	-1,004	0,741	5,060	-0,737
Money laundering	-2,453	-0,377	28,086	-6,729
Prostitution	-0,081	0,009	0,438	-0,086
Smuggling	-0,012	0,013	-0,088	-0,006
Threats	-2,535	2,068	-9,125	-1,418

Usury	0,687	0,503	-21,516	-0,850
Corruption in public acts	2,102	-1,473	-55,867	1,696
Instigation to corrupt	-0,397	-2,336	19,441	-1,327
Judicial corruption	9,423	-5,595	-26,330	1,178
Kidnapping for extortion purpose	-0,225	0,068	-0,757	-0,220

Table 2: Factor Loadings computed following Banbura and Modugno (2014)

	Italy	North	Centro	South
Bribery	12,71%	25,49%	14,73%	0,09%
Corruption for an action against official duties	0,00%	13,20%	0,95%	23,20%
Criminal association	0,47%	0,23%	0,20%	0,36%
Drugs	0,00%	0,00%	0,01%	0,00%
Extortions	0,05%	0,01%	0,00%	0,07%
Homicide by Mafia	0,02%	0,03%	0,01%	0,04%
Mafia type Association	0,81%	0,76%	0,39%	0,76%
Money laundering	4,86%	0,20%	11,94%	63,19%
Prostitution	0,01%	0,00%	0,00%	0,01%
Smuggling	0,00%	0,00%	0,00%	0,00%
Threats	5,19%	5,91%	1,26%	2,80%
Usury	0,38%	0,35%	7,01%	1,01%
Corruption in public acts	3,57%	3,00%	47,26%	4,01%
Instigation to corrupt	0,13%	7,55%	5,72%	2,46%
Judicial corruption	71,75%	43,27%	10,50%	1,94%
Kidnapping for extortion purpose	0,04%	0,01%	0,01%	0,07%

Table 3: Square of factor loadings computed following Banbura and Modugno (2014), as percentage of the total.

		Share F	Share G	Share H	Share Z
Center	**Lazio**	0,10	0,09	0,10	0,71
	Marche	0,08	0,07	0,13	0,72
	Toscana	0,10	0,09	0,09	0,72
	Umbria	0,19	0,16	0,10	0,55
North	**Emilia Romagna**	0,17	0,07	0,07	0,69
	Friuli Venezia Giulia	0,10	0,04	0,17	0,69
	Liguria	0,21	0,09	0,10	0,61
	Lombardia	0,20	0,09	0,03	0,68
	Piemonte	0,20	0,08	0,06	0,66
	Trentino Alto Adige	0,17	0,07	0,06	0,70
	Valle D'Aosta	0,15	0,06	0,09	0,70
	Veneto	0,19	0,08	0,06	0,66
South	**Abruzzo**	0,02	0,13	0,13	0,71
	Basilicata	0,00	0,02	0,25	0,72
	Calabria	0,03	0,14	0,15	0,69
	Campania	0,01	0,07	0,22	0,70
	Molise	0,00	0,02	0,22	0,75
	Puglia	0,01	0,03	0,22	0,75
	Sardegna	0,01	0,04	0,23	0,72
	Sicilia	0,01	0,06	0,21	0,72

Table 4: ShareF, ShareG, ShareH, ShareZ denote the average variance share across all variables in the block due to aggregate, block-level, sub-block-level and idiosyncratic shocks respective

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Commenta [6]: It is unclear what Share F, G, H, and Z are. The text provides some details by clarifying as follows "aggregate (Italy-wide), block-specific (Macro), and subblock-specific (Regional) components as well as idiosyncratic noise (IdioNoise)" . Can this be added to the column lables in the table to make it easier to read?

Dependent var.	Mafia Rank Index						Mafia Mean Index					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Regressors												
Lagged Mafia Index	0.60**	0.72***	0.72***	0.74***	0.72***	0.69***	0.87***	0.96***	0.88***	0.95***	0.95***	0.91***
	(0.27)	(0.17)	(0.06)	(0.20)	(0.09)	(0.10)	(0.08)	(0.08)	(0.06)	(0.07)	(0.09)	(0.09)
Gini	45.96						76.51					
	(61.63)						(56.72)					
Atkinson		2.10						33.16				
		(19.49)						(25.84)				
P90/P10			2.47**						3.53***			
			(0.90)						(1.04)			
P75/P25				8.19						19.70**		
				(7.37)						(8.08)		
P90/P50					8.44*						19.80**	
					(4.20)						(8.50)	
P75/P50						17.78**						48.77***
						(8.13)						(16.61)
period3	6.78***	7.56***	6.36***	7.11***	6.45***	7.51***	-0.68	-0.98	-1.08	-0.06	-0.49	0.68
	(1.67)	(1.82)	(1.46)	(1.55)	(1.38)	(1.04)	(0.98)	(1.34)	(1.06)	(1.17)	(1.05)	(1.18)
period4	11.55***	11.48***	10.88***	11.32***	10.07***	11.18***	0.42	0.08	0.77	2.07*	0.64	1.37
	(1.57)	(1.95)	(1.56)	(1.79)	(1.73)	(1.57)	(0.87)	(0.94)	(1.01)	(1.01)	(1.08)	(1.05)
period5	4.85*	4.18	3.85**	3.86*	4.27*	4.64***	0.55	-0.02	0.96	1.22	2.08	1.41
	(2.67)	(2.64)	(1.74)	(2.20)	(2.18)	(1.47)	(2.66)	(2.54)	(2.73)	(2.73)	(2.69)	(2.73)
period6	5.65***	5.44**	4.43**	5.05***	4.93***	6.21***	-0.11	-1.87	-1.01	-0.04	1.12	1.06
	(1.55)	(2.04)	(1.57)	(1.37)	(1.51)	(1.39)	(1.45)	(2.31)	(1.39)	(1.28)	(1.37)	(1.38)
Constant	-6.55	2.46	-5.71	-13.01	-11.58	-20.20*	-15.51	-6.46	-7.02	-35.74**	-35.22*	-63.34**
	(11.44)	(4.88)	(3.59)	(9.30)	(7.07)	(9.81)	(18.42)	(10.30)	(6.28)	(16.38)	(17.73)	(25.81)
Observations	95	95	95	95	95	95	95	95	95	95	95	95
Number of Regions	19	19	19	19	19	19	19	19	19	19	19	19
Hansen test p-value	0.818	0.730	0.925	0.761	0.986	0.749	0.540	0.387	0.446	0.555	0.554	0.511

Table 7: This tables presents dynamic panel regressions of Mafia Rank Index and Mafia Mean Index based on Calderoni (2011) on alternative income inequality indices. All results are based on the baseline sample of 5-year averages. All models control for fixed effects and time period effects. Estimation is based on system GMM (Blundell and Bond (1998) using instruments up to the 4th lag. Each cell reports the coefficient estimates and robust standard errors in the parenthesis. ***, **, and * denote significance of the regression coefficient at 1%, 5%, and 10%

Dependent var.	Mafia Rank Index						Mafia Mean Index					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Regressors												
Lagged Mafia Index	0.80***	0.46***	0.63***	0.75***	0.73***	0.74***	0.91***	0.99***	1.04***	0.98***	0.93**	0.94***
	(0.09)	(0.15)	(0.16)	(0.12)	(0.10)	(0.13)	(0.20)	(0.20)	(0.17)	(0.17)	(0.33)	(0.18)
Gini	41.41						179.06**					
	(42.08)						(71.75)					
Atkinson		82.54*						151.78**				
		(42.77)						(61.62)				
P90/P10			5.65						13.85***			
			(5.74)						(4.51)			
P75/P25				10.26						33.27		
				(14.35)						(19.90)		
P90/P50					2.72						50.19	
					(6.86)						(30.88)	
P75/P50						53.59**						98.06**
						(24.95)						(37.02)
period3	8.30***	6.66***	6.97***	8.28***	7.61***	6.09***	1.62	1.11	0.48	0.42	-0.39	-0.91
	(1.35)	(1.72)	(1.50)	(1.42)	(1.21)	(1.34)	(2.20)	(2.47)	(2.12)	(1.72)	(2.10)	(1.80)
period4	11.94***	10.19***	10.99***	11.98***	11.41***	9.82***	1.51	1.72	-0.29	0.11	0.87	-0.53
	(2.25)	(2.63)	(1.97)	(2.66)	(2.38)	(1.75)	(2.10)	(2.39)	(2.67)	(2.13)	(2.09)	(1.86)
period5	4.38*	7.88***	5.51*	4.67	4.24*	3.33	3.17	4.58	3.98	1.11	4.83	0.47
	(2.35)	(2.61)	(2.67)	(2.72)	(2.07)	(2.21)	(4.70)	(4.27)	(4.71)	(4.51)	(4.64)	(3.68)
period6	5.61***	6.94***	6.00***	5.71**	5.50***	5.36***	2.57	1.44	0.22	0.57	3.64	1.81
	(1.71)	(1.47)	(1.64)	(2.00)	(1.76)	(1.50)	(2.41)	(2.78)	(2.18)	(2.57)	(3.33)	(1.78)
Constant	-9.86	-5.05	-11.31	-16.27	-1.94	-68.27**	-42.68	-30.40	-45.61**	-58.36	-88.77	-128.52**
	(11.01)	(11.76)	(15.53)	(25.23)	(12.39)	(32.19)	(25.42)	(19.12)	(19.59)	(40.67)	(71.94)	(57.21)
Observations	95	95	95	95	95	95	95	95	95	95	95	95
Number of Regions	19	19	19	19	19	19	19	19	19	19	19	19
Hansen test p-value	0.983	0.187	0.979	0.986	0.968	0.998	0.103	0.0729	0.0866	0.0571	0.169	0.232

Table 8: This tables presents dynamic panel regressions of Mafia Rank Index and Mafia Mean Index based on Calderoni (2011) on alternative consumption inequality indices. All results are based on the baseline sample of 5-year averages. All models control for fixed effects and time period effects. Estimation is based on system GMM (Blundell and Bond (1998) using instruments up to the 4th lag. Each cell reports the coefficient estimates and robust standard errors in the parenthesis. ***, **, and * denote significance of the regression coefficient at 1%, 5%, and 10%

Dependent var.	Mafia Rank Index						Mafia Mean Index					
Dependent var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Regressors												
Lagged Mafia Index	0.42**	0.42**	0.35	0.76***	0.50	0.47	0.86***	0.85***	0.92***	0.84***	0.92***	0.84***
	(0.17)	(0.15)	(0.25)	(0.08)	(0.31)	(0.29)	(0.08)	(0.09)	(0.16)	(0.09)	(0.08)	(0.07)
Gini	78.50						32.85					
	(72.39)						(46.96)					
Lagged Gini	41.35						70.80**					
	(31.44)						(33.06)					
Atkinson		57.76						20.39				
		(60.21)						(41.88)				
Lagged Atkinson		48.23*						53.51*				
		(26.09)						(29.15)				
P90/P10			1.25						15.28***			
			(5.22)						(4.30)			
Lagged P90/P10			3.81*						-2.84			
			(2.13)						(3.46)			
P75/P25				-3.80						3.53		
				(13.20)						(15.78)		
Lagged P75/P25				20.19*						14.98*		
				(11.46)						(8.27)		
P90/P50					0.32						21.79**	
					(12.23)						(9.80)	
Lagged P90/P50					13.74*						1.97	
					(7.27)						(8.22)	
P75/P50						31.88						86.02*
						(90.24)						(41.14)
Lagged P75/P50						5.63						-7.93
						(43.36)						(26.16)
period3	5.55**	5.09***	5.00***	5.37**	6.00***	5.48**	-1.43	-1.28	1.05	-0.89	0.06	-1.28
	(2.11)	(1.45)	(1.57)	(2.19)	(1.44)	(2.08)	(1.16)	(1.24)	(1.54)	(1.23)	(1.08)	(1.37)
period4	10.05***	9.98***	10.75***	8.70***	9.72***	10.42***	-0.97	-0.85	1.03	-0.59	-0.06	-0.71
	(1.97)	(1.83)	(1.49)	(1.96)	(2.64)	(2.16)	(1.10)	(1.23)	(2.19)	(1.05)	(1.45)	(1.81)
period5	7.22**	7.15**	6.45**	1.48	4.12	5.84**	-0.47	-0.33	4.16	-0.57	2.31	1.70
	(3.10)	(2.87)	(2.97)	(2.24)	(4.51)	(2.42)	(3.08)	(3.07)	(3.18)	(2.43)	(2.79)	(3.07)
period6	7.85***	7.37***	7.49***	4.04**	6.91**	6.67***	0.54	0.37	1.11	0.20	2.27	0.85
	(1.87)	(1.71)	(1.77)	(1.74)	(3.01)	(1.69)	(1.87)	(1.76)	(1.23)	(1.56)	(1.82)	(1.61)
Constant	-17.60	-6.92	-1.11	-24.51	-15.19	-39.62	-18.61	-5.43	-35.72**	-23.77	-39.73**	-96.18**
	(19.88)	(13.03)	(16.68)	(20.99)	(30.31)	(73.91)	(14.26)	(10.20)	(15.23)	(25.63)	(14.84)	(37.50)
Observations	95	95	95	95	95	95	95	95	95	95	95	95
Number of Regions	19	19	19	19	19	19	19	19	19	19	19	19
Hansen test p-value	0.360	0.405	0.518	0.675	0.549	0.399	0.966	0.961	0.344	0.981	0.910	0.989

Table 9: This tables presents dynamic panel regressions of Mafia Rank Index and Mafia Mean Index based on Calderoni (2011) on alternative inequality indices. All results are based on the baseline sample of 5-year averages. All models control for fixed effects and time period effects. Estimation is based on system GMM (Blundell and Bond (1998) using instruments up to the 4th lag. Each cell reports the coefficient estimates and robust standard errors in the parenthesis. ***, **, and * denote significance of the regression coefficient at 1%, 5%, and 10%.

Dependent var	Mafia Rank Index								Mafia Mean Index							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Regressors																
Lagged Mafia Index	0.93***	0.92***	0.85***	0.93***	0.84***	0.92***	0.85***	0.84***	0.67***	0.65***	0.62***	0.70***	0.66***	0.67***	0.68***	0.65***
	(0.06)	(0.06)	(0.09)	(0.06)	(0.08)	(0.07)	(0.07)	(0.11)	(0.05)	(0.08)	(0.10)	(0.05)	(0.10)	(0.06)	(0.08)	(0.10)
P90/P10	0.63	-1.99	-0.00	-2.42	2.49	-1.88	-2.12	0.56	1.15	1.16	0.66	0.12	0.48	0.91	1.43	0.85
	(1.08)	(2.37)	(3.31)	(1.86)	(3.22)	(1.67)	(2.59)	(3.10)	(1.38)	(1.47)	(1.94)	(1.52)	(1.88)	(1.19)	(1.50)	(2.01)
Lagged P90/P10	3.66***	2.06*	-0.07	2.09**	7.52***	1.12	1.22	0.13	1.76	1.52	1.67	1.60	0.89	0.75	0.46	1.47
	(1.18)	(1.11)	(1.78)	(0.98)	(2.28)	(0.92)	(1.06)	(1.98)	(2.07)	(2.15)	(2.26)	(1.84)	(2.34)	(1.74)	(1.88)	(2.39)
Economic activity rate		-0.79***	-0.60*	-0.71***	-1.54***	-0.75***	-0.86***	-0.77**		-0.20	-0.31	-0.21*	-0.19	-0.24	-0.21	-0.35
		(0.22)	(0.29)	(0.20)	(0.21)	(0.20)	(0.25)	(0.30)		(0.15)	(0.26)	(0.11)	(0.21)	(0.14)	(0.15)	(0.25)
Secondary Education level			-0.42								0.08					
			(0.45)								(0.44)					
Compensation of employees				26.97								-32.20				
				(54.31)								(29.36)				
Long-run unemployment					-3.12***								0.30			
					(0.72)								(0.55)			
Gross fixed capital formation						23.15								-3.32		
						(37.95)								(30.03)		
Total hours worked							-314.74**								2.52	
							(144.53)								(144.82)	
Part. in education and training								-0.19								1.08
								(3.40)								(2.43)
period3	-1.10	-1.64	0.00	-0.88	6.92***	-2.56	0.82	0.00	5.66***	0.93	0.00	1.71	0.42	1.53	1.21	0.00
	(1.23)	(2.67)	(0.00)	(2.61)	(2.24)	(3.36)	(2.74)	(0.00)	(1.61)	(2.31)	(0.00)	(1.90)	(3.48)	(2.60)	(2.27)	(0.00)
period4	-1.84	-2.31	55.15**	-2.31	0.97	-2.76	1.22	47.61*	9.05***	4.30*	3.76	4.82**	4.03	5.00*	5.01*	5.38
	(1.21)	(2.16)	(24.61)	(2.24)	(1.63)	(2.92)	(2.98)	(24.54)	(2.12)	(2.21)	(3.99)	(1.93)	(2.56)	(2.72)	(2.57)	(5.58)
period5	-0.12		57.85**					49.36*	3.84*		-0.48					-0.17
	(2.34)		(24.64)					(26.40)	(1.85)		(2.78)					(2.85)
period6	-0.37	1.39	59.12**	2.25	7.17***	2.15	-2.42	49.39	4.23***	0.40	0.00	0.28	0.04	0.43	0.30	0.00
	(1.39)	(3.24)	(27.69)	(2.85)	(1.87)	(2.61)	(3.44)	(29.45)	(1.44)	(1.84)	(0.00)	(2.02)	(2.16)	(2.02)	(3.11)	(0.00)
Constant	-11.42	47.21**	0.00	43.43**	67.91***	48.34***	57.95**	0.00	-4.39	11.79	17.63	14.64	14.70	16.73	14.37	14.72
	(6.67)	(18.96)	(0.00)	(15.77)	(20.51)	(15.80)	(21.67)	(0.00)	(5.10)	(12.34)	(18.20)	(9.83)	(14.42)	(11.94)	(11.35)	(18.27)
Observations	95	72	55	72	70	72	72	55	95	72	55	72	70	72	72	55
Number of Regions	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19
Hansen test p-value	0.410	0.456	0.167	0.943	0.902	0.987	0.997	0.0938	0.867	0.628	0,309	0.971	0.739	0.972	0.971	0.376

Table 10: This table presents dynamic panel regressions of the Mean Mafia Index, which is the Mafia Rank Index based on Calderoni (2011), on P90/P10 ratio and other determinants. All results are based on the baseline sample of 5-year averages. All models control for fixed effects and time period effects. Each cell reports the coefficient estimates and robust standard errors in the parenthesis. All regression models include fixed effects and time effects. Estimation is based on system GMM (Blundell and Bond (1998) using instruments up to the 4th lag. ***, **, and * denote significance of the regression coefficient at 1%, 5%, and 10%.

Dependent variable	Hierarchical Dynamic Factor Analysis						EM Algorithm					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Regressors												
Lagged Mafia Index	-0.43	-0.41	-0.37	-0.37*	-0.32*	-0.26*	-0.09*	-0.11	-0.16*	-0.12	-0.11	-0.12**
	(0.25)	(0.25)	(0.32)	(0.19)	(0.17)	(0.15)	(0.05)	(0.08)	(0.08)	(0.08)	(0.07)	(0.05)
ΔGini	1.42**						2.08*					
	(0.64)						(1.02)					
ΔAtkinson		1.16**						1.51*				
		(0.53)						(0.77)				
ΔP90/P10			0.15*						0.14**			
			(0.08)						(0.07)			
ΔP75/P25				0.08						0.23		
				(0.16)						(0.26)		
ΔP90/P50					0.34**						0.24***	
					(0.14)						(0.07)	
ΔP75/P50						-0.52						1.18
						(0.40)						(1.19)
period3	0.01	0.00	-0.00	-0.03*	-0.00	-0.04	0.06	0.09	0.07	0.02	0.03	0.03
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.04)	(0.06)	(0.05)	(0.07)	(0.04)	(0.08)
period4	0.01	0.01	0.00	-0.02	0.01	-0.03	0.04	0.06	0.04	0.01	0.02	-0.01
	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)	(0.07)	(0.05)	(0.07)	(0.06)	(0.07)
period5	0.03	0.03	0.04	-0.02	0.04	-0.05***	0.09	0.10	0.10*	0.05	0.06	0.06
	(0.04)	(0.04)	(0.06)	(0.02)	(0.04)	(0.02)	(0.05)	(0.06)	(0.05)	(0.07)	(0.04)	(0.08)
period6	0.01	0.00	-0.01	-0.01	0.02	-0.02	0.03	0.02	0.01	-0.02	0.01	0.00
	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)
Constant	-0.02	-0.01	-0.01	0.01	-0.01	0.03*	-0.05	-0.06	-0.05	-0.01	-0.03	-0.02
	(0.02)	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.06)
Observations	95	95	95	95	95	95	95	95	95	95	95	95
Number of Regions	19	19	19	19	19	19	19	19	19	19	19	19
Hansen test p-value	0.280	0.297	0.574	0.445	0.553	0.307	0.624	0.219	0.987	0.210	0.404	0.461

Table 11: The tables presents regressions of two latent factors on alternative inequality of consumption indices. In Panel A, we have the results of a factor constructed using a hierachical dynamic factor methodology , while in Panel B we show the results of a dynamic factor estimated by using a modified Expectation Maximisation (EM) algorithm. Given that the latent factors are constructed on transformed data to endure stationarity (growth rates) we also transform the regressors into first differences, too. All results are based on the baseline sample of 5-year averages. Each cell

reports the coefficient estimates and robust standard errors in the parenthesis. All regressions control for fixed effects and time period effects. ***, **, and * denote significance of the regression coefficient at 1%, 5%, and 10%

Dependent variable	Mafia Mean Index (Type I, II)			Mafia Rank Index (Type I, II)		
Regressors	(1)	(2)	(3)	(4)	(5)	(6)
Absolute Upward Mobility: Expected Rank	-60.35***			-53.19**		
	(9.776)			(20.72)		
Absolute Upward Mobility: Q1Q5		-50.32***			-39.19**	
		(9.324)			(18.56)	
Relative Mobility			116.7***			179.2***
			(23.62)			(42.37)
Constant	48.81***	27.42***	1,25	75.18***	55.65***	20.44***
	(4.778)	(1.471)	(3.901)	(9.849)	(2.842)	(7.253)
Observations	95	95	95	95	95	95
R-squared	0,269	0,218	0,235	0,064	0,041	0,17

Table 14: The tables presents cross-sectional regressions of three alternative socio-economic mobility measures. All results are based on the baseline sample of 5-year averages. Each cell reports the coefficient estimates and robust standard errors in the parenthesis. ***, **, and * denote significance of the regression coefficient at 1%, 5%, and 10%.

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