Social capital and economic growth in Europe: nonlinear trends and heterogeneous regional effects

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Social capital, institutions and economic performance in times of crisis
1. Introduction

2. Empirical methodology

3. Model, sample and descriptive statistics

4. Results, parametric regressions

5. Results, nonparametric regressions

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Introduction
Social capital as a growth theory

- Theories explaining economic growth: geography, demography, institutions, education, financial development and... **social capital**
- Durlauf and Fafchamfs (2005): “A set of informal forms of institutions and organizations based on social relationships, networks and associations that create shared knowledge, mutual trust, social norms and unwritten rules”
- Some **classical contributions** are Putnam (1993); Knack and Keefer (1997); Zak and Knack (2001).
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- Reduces monitoring costs
- Facilitates complex agreements by mitigating information asymmetries
- Eases knowledge diffusion and innovation processes
- Other (indirect) effects: financial development (Guiso et al., 2004), human capital (Bjørnskov, 2009; Dearmon and Grier, 2011), investment (Zak and Knack, 2001; Dearmon and Grier, 2011; Peiró-Palomino and Tortosa-Ausina, 2013b) or trade (Guiso et al., 2009)
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Considering ECE regions is important for some reasons:

- Social capital in ECE regions is lower than in Western regions. Some authors (see Rose, 2000; Paldam and Svendsen, 2001; Zükowski, 2007 and Fidrmuc and Gërxbhani, 2008) suggest this is a consequence of the communist experience, which modified social patterns and negatively affected social capital.
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Analyzing the role of social capital in the enlarged EU (237 regions during the period 1995–2007)

- Two indicators: trust and associational life (active participation)
- Use of nonparametric regression which permits shed light on:
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Empirical methodology

Parametric and nonparametric regressions

- **Parametric (OLS)** regressions

\[
Y_i = \beta_0 + \sum_{j=1}^{V} \beta_j Z_{ji} + \epsilon_i, \ i = 1, 2, ... n,
\]  

- **Nonparametric (kernel)** regressions

\[
Y_i = m(Z_i) + \epsilon_i, \ i = 1, 2, ... n,
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- \( m(.) \) is an unknown smooth function capturing the conditional relationship between the dependent and the independent variables in the model
- Some alternatives to compute \( m(Z_i) \) based on the methods proposed by Li and Racine (2004) and Racine and Li (2004)
- Generalized product kernel methods, valid for both continuous and categorical variables
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- **Nonparametric (kernel) regressions**

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Local-Constant Least Squares (LCLS)

- Particularly useful to identify **relevancy** of the regressors
- Estimates \( m(.) \) by calculating a local weighted average of the dependent variable \( Y_i \) considering the observations with similar values of the independent variables \( Z_i \)
- The **bandwidths** determine the quantity of averaged observations around each point \( z_i \)
- The estimator obeys to the following expression

\[
\hat{m}(z) = \frac{\sum_{i=1}^{n} y_i \prod_{s=1}^{q} K \left( \frac{z_{si} - z_s}{h_s} \right)}{\sum_{i=1}^{n} \prod_{s=1}^{q} K \left( \frac{z_{si} - z_s}{h_s} \right)}
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Nonparametric regression, estimation alternatives

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- Suitable to detect **nonlinearities** of the regressors
- It computes a weighted least-squares regression around every point $z_i$.
- Weights established by a kernel function and a bandwidth vector such that those observations closer to $z_i$ receive more weight
- The estimator obeys to the following expression

$$Y_i \approx m(z) + (z_i^c - z^c)\beta(z^c) + \epsilon_i$$  \hspace{1cm} (4)

$$\hat{\delta}(z) = [Z'K(z)Z]^{-1}Z'K(z)y$$  \hspace{1cm} (5)

Following Li and Racine (2007), a second-order Gaussian kernel is selected for continuous variables whereas for categorical variables the choice is the Aitchison and Aitken (1976) kernel.
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Independently of the approach, the important choice is not the kernel, but the bandwidth (in general in all nonparametric procedures).

Unappropriate bandwidths may produce estimates with low variance and high bias (undersmoothing), or high variance and low bias (oversmoothing).

Bandwidths are selected using least-squares cross-validation (LSCV), an automated bandwidth selection procedure.

The bandwidths not only determine the degree of smoothing:

- In LCLS when the bandwidth associated to one regressor hits its upper bound (UB), it denotes irrelevancy.
- In LLLS when the bandwidth associated to one regressor hits its upper bound (UB), it denotes linearity.
- UB are defined as two standard deviations for continuous variables and $(q_s - 1)/q_s$ for categorical variables (with $q_s$ the number of values the variable can take).
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  - In LCLS when the bandwidth associated to one regressor hits its upper bound (UB), it denotes irrelevancy
  - In LLLS when the bandwidth associated to one regressor hits its upper bound (UB), it denotes linearity
  - UB are defined as two standard deviations for continuous variables and \((q_s - 1)/q_s\) for categorical variables (with \(q_s\) the number of values the variable can take)
Independently of the approach, the important choice is not the kernel, but the bandwidth (in general in all nonparametric procedures)

Unappropriate bandwidths may produce estimates with low variance and high bias (**undersmoothing**), or high variance and low bias (**oversmoothing**)

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Empirical methodology
Nonparametric regression, estimation alternatives

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Outline

1. Introduction
2. Empirical methodology
3. Model, sample and descriptive statistics
4. Results, parametric regressions
5. Results, nonparametric regressions
6. Conclusions
Sample of 237 European regions (NUTS 2)


Neoclassical growth equation (Solow, 1957) augmented with social capital

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ACTIVE: percentage of people who voluntarily participate in at least one association (from 15 different). Source: EVS (1999)

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Different models (1–5) where the variables are included sequentially
Data constraints on the social capital variables. (NUTS 1 level aggregation)
## Descriptive statistics

### Sample summary, ECE and non-ECE regions

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<td>ECE regions</td>
<td>Non ECE regions</td>
<td>ECE regions</td>
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<tr>
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<td>Mean</td>
<td>s.d.</td>
<td>Obs.</td>
<td>Mean</td>
<td>s.d.</td>
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<td>0.050</td>
<td>0.031</td>
<td>46</td>
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<td>0.031</td>
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<td>46</td>
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</table>
Outline

1. Introduction
2. Empirical methodology
3. Model, sample and descriptive statistics
4. Results, parametric regressions
5. Results, nonparametric regressions
6. Conclusions
### Results, parametric regressions

**Ordinary least squares (OLS) estimation**

<table>
<thead>
<tr>
<th>Dependent variable: GDP growth ($\text{GGDP}$)</th>
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<tbody>
<tr>
<td>Model 1</td>
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<tr>
<td>(Intercept)</td>
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<tr>
<td>(0.018)</td>
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<tr>
<td>$\log(\text{GDP}_0)$</td>
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<tr>
<td>(0.347)</td>
</tr>
<tr>
<td>$\text{GPOP}$</td>
</tr>
<tr>
<td>(0.244)</td>
</tr>
<tr>
<td>$\text{GFCF}$</td>
</tr>
<tr>
<td>(0.028)</td>
</tr>
<tr>
<td>$\text{HC}$</td>
</tr>
<tr>
<td>(0.017)</td>
</tr>
<tr>
<td>$\text{TRUST}$</td>
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<tr>
<td>(0.011)</td>
</tr>
<tr>
<td>$\text{ACTIVE}$</td>
</tr>
<tr>
<td>(0.064)</td>
</tr>
<tr>
<td>$\text{CAPITAL}$</td>
</tr>
<tr>
<td>(0.004)</td>
</tr>
<tr>
<td>$N$</td>
</tr>
<tr>
<td>$R^2$ (Adjusted)</td>
</tr>
<tr>
<td>$F_{\text{STAT}}$</td>
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<tr>
<td>Time control</td>
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</table>

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### Results, parametric regressions

Tests of appropriateness of the parametric models Hsiao et al. (2007)

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
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<td>( Jn )-statistic</td>
<td>12.828 (0.000)</td>
<td>10.580 (0.000)</td>
<td>5.676 (0.000)</td>
<td>9.820 (0.000)</td>
<td>9.764 (0.000)</td>
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Results, nonparametric regressions
Bandwidths for LCLS and LLLS estimators

<table>
<thead>
<tr>
<th>Variables/method</th>
<th>UB</th>
<th>LCLS</th>
<th>LLLS</th>
<th>UB</th>
<th>LCLS</th>
<th>LLLS</th>
<th>UB</th>
<th>LCLS</th>
<th>LLLS</th>
<th>UB</th>
<th>LCLS</th>
<th>LLLS</th>
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</thead>
<tbody>
<tr>
<td>In(GDP$_0$)</td>
<td>1.622</td>
<td>0.134</td>
<td>0.276</td>
<td>0.154</td>
<td>0.205</td>
<td>0.242</td>
<td>0.1528</td>
<td>0.261</td>
<td>0.287</td>
<td>0.748</td>
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<tr>
<td>GPOP</td>
<td>0.012</td>
<td>0.007</td>
<td>0.008</td>
<td>1,809</td>
<td>0.005</td>
<td>0.007</td>
<td>22,195</td>
<td>0.003</td>
<td>0.010</td>
<td>1,364</td>
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<tr>
<td>GFCF</td>
<td>0.106</td>
<td>0.016</td>
<td>0.057</td>
<td>149,738</td>
<td>0.033</td>
<td>0.042</td>
<td>383,800</td>
<td>0.025</td>
<td>1,149,916</td>
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<tr>
<td>HC</td>
<td>0.173</td>
<td>0.019</td>
<td>0.052</td>
<td>0.270</td>
<td>0.421</td>
<td>0.033</td>
<td>0.066</td>
<td>0.269</td>
<td>0.147</td>
<td>0.640</td>
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<td>TRUST</td>
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<td>2.05e-06</td>
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<td>1.16e-04</td>
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<td>0.005</td>
<td>0.029</td>
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<tr>
<td>ACTIVE</td>
<td>0.043</td>
<td>0.007</td>
<td>0.012</td>
<td>0.017</td>
<td>0.027</td>
<td>3.0e-04</td>
<td>0.024</td>
<td></td>
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<tr>
<td>CAPITAL</td>
<td>0.500</td>
<td></td>
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<td>0.499</td>
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<tr>
<td>Time</td>
<td>0.500</td>
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<td>0.007</td>
<td>0.024</td>
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</table>

Dependent variable: GDP growth ($GGDP$)
Results, nonparametric regressions
Social capital indicators in Model 5

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Results, nonparametric regressions
Control variables in Model 5

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### Results, nonparametric regressions

**LLLS quartile estimates for the continuous regressors**

Dependent variable: GDP growth ($GGDP$)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\ln(GDP_0)$</td>
<td>-0.069</td>
<td>-0.047</td>
<td>-0.030</td>
<td>-0.071</td>
<td>-0.052</td>
<td>-0.040</td>
<td>-0.057</td>
<td>-0.041</td>
<td>-0.023</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.008)</td>
<td>(0.006)</td>
<td>(0.005)</td>
<td>(0.003)</td>
<td>(0.002)</td>
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<tr>
<td>$GPOP$</td>
<td>0.054</td>
<td>0.393</td>
<td>0.719</td>
<td>0.141</td>
<td>0.577</td>
<td>0.973</td>
<td>-0.280</td>
<td>0.116</td>
<td>0.989</td>
</tr>
<tr>
<td></td>
<td>(0.213)</td>
<td>(0.097)</td>
<td>(0.210)</td>
<td>(0.338)</td>
<td>(0.139)</td>
<td>(0.202)</td>
<td>(0.114)</td>
<td>(0.214)</td>
<td>(0.277)</td>
</tr>
<tr>
<td>$GFCF$</td>
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<td>-0.091</td>
<td>0.025</td>
<td>-0.289</td>
<td>-0.142</td>
<td>0.027</td>
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<td>(0.040)</td>
<td>(0.034)</td>
<td>(0.006)</td>
<td>(0.033)</td>
<td>(0.015)</td>
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<td>$HC$</td>
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<td>(0.041)</td>
<td>(0.018)</td>
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<td>(0.024)</td>
<td>(0.010)</td>
<td>(0.048)</td>
<td>(0.025)</td>
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<tr>
<td>$TRUST$</td>
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<td></td>
<td>(0.014)</td>
<td>(0.011)</td>
<td>(0.010)</td>
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<tr>
<td>$ACTIVE$</td>
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Time/capital controls: No
## Results, nonparametric regressions

### LLLS quartile estimates for the continuous regressors

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<tr>
<th>Variables</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
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<tbody>
<tr>
<td>$\ln(GDP_0)$</td>
<td>-0.052</td>
<td>-0.034</td>
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<td>(0.011)</td>
<td>(0.003)</td>
<td>(0.004)</td>
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<td>$GFCF$</td>
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<td></td>
<td>(0.067)</td>
<td>(0.087)</td>
<td>(0.115)</td>
<td>(0.156)</td>
<td>(0.009)</td>
<td>(0.023)</td>
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<td>$HC$</td>
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<td>(0.005)</td>
<td>(0.017)</td>
<td>(0.012)</td>
<td>(0.003)</td>
<td>(0.011)</td>
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<td>(0.037)</td>
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<td>0.322</td>
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<tr>
<td></td>
<td>(0.120)</td>
<td>(0.050)</td>
<td>(0.128)</td>
<td>(0.041)</td>
<td>(0.094)</td>
<td>(0.086)</td>
</tr>
</tbody>
</table>

|            | 404      | 404      |          |          |          |          |
| $N$        |          |          |          |          |          |          |
| $R^2$      | 0.958    |          |          | 0.958    |          |          |
| Time/capital controls | No | Yes |
Results, nonparametric regressions

Densities of the estimated coefficients in Model 5, Sheather and Jones (1991)

Peiró-Palomino and Tortosa-Ausina
Workshop on Social Capital
Valencia, 24th October 2014
Results, nonparametric regressions

Densities of the estimated coefficients in Model 5, Sheather and Jones (1991)
## Results, nonparametric regression

LLLS quartile estimates for the social capital variables in Model 5 across particular groups of regions

<table>
<thead>
<tr>
<th>Split/variable</th>
<th>TRUST</th>
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<th></th>
<th>TRUST</th>
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<tr>
<td></td>
<td>Q1</td>
<td>Q2</td>
<td>Q3</td>
<td>Q1</td>
<td>Q2</td>
<td>Q3</td>
</tr>
<tr>
<td>Below median (\ln(GDP_0))</td>
<td>-0.081</td>
<td>0.041</td>
<td>0.097</td>
<td>0.055</td>
<td>0.288</td>
<td>0.592</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.014)</td>
<td>(0.025)</td>
<td>(0.103)</td>
<td>(0.077)</td>
<td>(0.097)</td>
</tr>
<tr>
<td>Above median (\ln(GDP_0))</td>
<td>-0.010</td>
<td>0.006</td>
<td>0.029</td>
<td>0.188</td>
<td>0.348</td>
<td>0.462</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.041)</td>
<td>(0.038)</td>
<td>(0.015)</td>
<td>(0.068)</td>
</tr>
<tr>
<td>Below median (GFCF)</td>
<td>-0.010</td>
<td>0.010</td>
<td>0.099</td>
<td>0.179</td>
<td>0.323</td>
<td>0.471</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.004)</td>
<td>(0.018)</td>
<td>(0.023)</td>
<td>(0.077)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>Above median (GFCF)</td>
<td>-0.034</td>
<td>0.018</td>
<td>0.069</td>
<td>0.097</td>
<td>0.348</td>
<td>0.559</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.019)</td>
<td>(0.016)</td>
<td>(0.062)</td>
<td>(0.016)</td>
<td>(0.080)</td>
</tr>
<tr>
<td>Below median (HC)</td>
<td>-0.035</td>
<td>0.025</td>
<td>0.090</td>
<td>0.076</td>
<td>0.369</td>
<td>0.545</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.017)</td>
<td>(0.011)</td>
<td>(0.050)</td>
<td>(0.045)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>Above median (HC)</td>
<td>-0.013</td>
<td>0.012</td>
<td>0.065</td>
<td>0.175</td>
<td>0.287</td>
<td>0.468</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.014)</td>
<td>(0.069)</td>
<td>(0.014)</td>
<td>(0.060)</td>
</tr>
<tr>
<td>Below median (TRUST)</td>
<td>-0.035</td>
<td>0.024</td>
<td>0.075</td>
<td>0.086</td>
<td>0.344</td>
<td>0.586</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.017)</td>
<td>(0.013)</td>
<td>(0.073)</td>
<td>(0.077)</td>
<td>(0.089)</td>
</tr>
<tr>
<td>Above median (TRUST)</td>
<td>-0.011</td>
<td>0.011</td>
<td>0.089</td>
<td>0.166</td>
<td>0.307</td>
<td>0.454</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.017)</td>
<td>(0.060)</td>
<td>(0.015)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Below median (ACTIVE)</td>
<td>-0.063</td>
<td>0.006</td>
<td>0.108</td>
<td>0.116</td>
<td>0.297</td>
<td>0.504</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.003)</td>
<td>(0.045)</td>
<td>(0.051)</td>
<td>(0.014)</td>
<td>(0.056)</td>
</tr>
<tr>
<td>Above median (ACTIVE)</td>
<td>-0.012</td>
<td>0.019</td>
<td>0.043</td>
<td>0.157</td>
<td>0.349</td>
<td>0.498</td>
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<td>(0.012)</td>
<td>(0.006)</td>
<td>(0.052)</td>
<td>(0.031)</td>
<td>(0.013)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>ECE regions</td>
<td>-0.150</td>
<td>-0.086</td>
<td>0.045</td>
<td>-1.338</td>
<td>0.212</td>
<td>0.815</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.019)</td>
<td>(0.029)</td>
<td>(0.064)</td>
<td>(0.104)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>Non ECE regions</td>
<td>-0.004</td>
<td>0.019</td>
<td>0.083</td>
<td>0.187</td>
<td>0.328</td>
<td>0.469</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.008)</td>
<td>(0.016)</td>
<td>(0.052)</td>
<td>(0.070)</td>
<td>(0.060)</td>
</tr>
</tbody>
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Results, nonparametric regressions

Densities of the estimated coefficients for TRUST in Model 5 across particular groups of regions, Sheather and Jones (1991)

Peiró-Palomino and Tortosa-Ausina

Workshop on Social Capital

Valencia, 24th October 2014
Results, nonparametric regressions

Densities of the estimated coefficients for ACTIVE in Model 5 across particular groups of regions, Sheather and Jones (1991)

- Below median income
- Above median income

- Below median investment
- Above median investment

- Below median education
- Above median education

- Below median trust
- Above median trust

- ECE regions
- Non ECE regions
Results, nonparametric regressions
Nonparametric comparison of the estimated densities for different subgroups in Model 5 (Li, 1996)

<table>
<thead>
<tr>
<th>Comparison</th>
<th>TRUST</th>
<th>ACTIVE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Below vs. above ( GDP_0 )</td>
<td>46.951</td>
<td>13.288</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
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<tr>
<td>Below vs. above ( GFCF )</td>
<td>17.757</td>
<td>7.163</td>
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<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Below vs. above ( HC )</td>
<td>12.338</td>
<td>12.150</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Below vs. above ( TRUST )</td>
<td>23.646</td>
<td>12.003</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Below vs. above ( ACTIVE )</td>
<td>2.768</td>
<td>0.271</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.393)</td>
</tr>
<tr>
<td>ECE vs. non ECE regions</td>
<td>36.520</td>
<td>59.054</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>
**Endogeneity** issues should not be a problem in the context of social capital due to the stability of social values over time.

Unfortunately, most of the referees in academic journals do not agree on this.

In the nonparametric framework, technical alternatives to deal with this problem are very recent and empirical applications of these methods virtually nonexistent (see, Henderson et al, 2013).

Here the Su and Ullah (2008) procedure is used. It consists of the following two steps:

- **Stage I**: LCLS estimation on the endogenous variables over a set of suitable instruments.
- **Stage II**: LLLS estimation on the original regression, including both the endogenous and the exogenous variables as well as the adjusted residuals from Stage I.

Selection of instruments: Nobel strategy by Henderson’s et al, (2013). The control variables instrument social capital.
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Results, nonparametric regressions
Dealing with endogeneity

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Selection of instruments: Nobel strategy by Henderson’s et al, (2013). The control variables instrument social capital.
### Results, nonparametric regressions

Dealing with endogeneity

<table>
<thead>
<tr>
<th>Variables/method</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(GDP&lt;sub&gt;0&lt;/sub&gt;)</td>
<td>1.622</td>
<td>0.134</td>
<td>0.276</td>
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<td>0.242</td>
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<td>GPOP</td>
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<td>0.008</td>
<td>0.1809</td>
<td>0.006</td>
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<tr>
<td>GFCF</td>
<td>0.106</td>
<td>0.016</td>
<td>0.057</td>
<td>0.033</td>
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<tr>
<td>HC</td>
<td>0.173</td>
<td>0.019</td>
<td>0.052</td>
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<td>TRUST</td>
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<td>2.05e-06</td>
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<td>ACTIVE</td>
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<td>0.007</td>
<td>0.012</td>
<td>0.017</td>
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<td>CAPITAL</td>
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<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Time</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Dependent variable: GDP growth (\(GGDP\))
Results, nonparametric regressions

IV estimation of Model 5 (Su and Ullah, 2008), bandwidths

<table>
<thead>
<tr>
<th></th>
<th>Stage I (LCLS)</th>
<th>Stage II (LLLS)</th>
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<tr>
<td></td>
<td>UB</td>
<td>D.V: TRUST</td>
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<tr>
<td>( \ln(GDP_0) )</td>
<td>1.622</td>
<td>0.111</td>
</tr>
<tr>
<td>GPOP</td>
<td>0.012</td>
<td>0.002</td>
</tr>
<tr>
<td>GFCF</td>
<td>0.106</td>
<td>0.117</td>
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<tr>
<td>HC</td>
<td>0.173</td>
<td>0.015</td>
</tr>
<tr>
<td>TRUST</td>
<td>0.278</td>
<td></td>
</tr>
<tr>
<td>ACTIVE</td>
<td>0.043</td>
<td></td>
</tr>
<tr>
<td>CAPITAL</td>
<td>0.500</td>
<td></td>
</tr>
<tr>
<td>Time</td>
<td>0.500</td>
<td></td>
</tr>
<tr>
<td>( \mu_{\text{TRUST}} )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \mu_{\text{ACTIVE}} )</td>
<td></td>
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</table>
### Results, nonparametric regression

IV estimation, LLLS quartile estimates for the continuous variables in the instrumented Model 5 (Su and Ullah, 2008)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
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</thead>
<tbody>
<tr>
<td>ln(GDP$_0$)</td>
<td>-0.057</td>
<td>-0.035</td>
<td>-0.016</td>
<td>-0.050</td>
<td>-0.039</td>
<td>-0.028</td>
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<td>GPOP</td>
<td>-0.152</td>
<td>0.168</td>
<td>0.663</td>
<td>-0.257</td>
<td>0.298</td>
<td>1.221</td>
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<tr>
<td>GFCF</td>
<td>-0.354</td>
<td>0.024</td>
<td>0.139</td>
<td>-0.288</td>
<td>0.006</td>
<td>0.105</td>
</tr>
<tr>
<td>HC</td>
<td>-0.012</td>
<td>0.031</td>
<td>0.099</td>
<td>-0.048</td>
<td>0.038</td>
<td>0.112</td>
</tr>
<tr>
<td>TRUST</td>
<td>-0.018</td>
<td>0.014</td>
<td>0.079</td>
<td>-0.046</td>
<td>0.034</td>
<td>0.121</td>
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<tr>
<td>ACTIVE</td>
<td>0.143</td>
<td>0.322</td>
<td>0.504</td>
<td>-0.183</td>
<td>0.298</td>
<td>0.976</td>
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<tr>
<td>N</td>
<td>404</td>
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<td>404</td>
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<tr>
<td>$R^2$</td>
<td>0.958</td>
<td>0.980</td>
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<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Conclusions

- The linear specification imposed by the parametric methods is not the true underlying relationship between the two indicators of social capital and growth.
- TRUST is not significant in the parametric analysis (in line with previous research for the European regions), but it is significant in the nonparametric one.
- ACTIVE is significant in both the parametric and the nonparametric estimation.
- The average coefficient provided by the parametric analysis simply does not reflect the effect of social capital in some regions.
- The greatest differences appear when comparing ECE and non-ECE regions.
- Some policy suggestions:
  - The existent stock of social capital in each region should be considered.
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