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

Outline

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- Theories explaining economic growth: geography, demography, institutions, education, financial development and...**social capital**
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- Some **classical contributions** are Putnam (1993); Knack and Keefer (1997); Zak and Knack (2001).
- Some **recent contributions** include Akçomak and Ter Weel, 2009; Dearmon and Grier (2009, 2011), Peiró-Palomino and Tortosa-Ausina (2013, 2014) Bjørnskov, (2006, 2012), Bjørnskov et al. (2013), Westlund et al. (2009, 2011, 2013).

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  - Facilitates complex agreements by mitigating information asymmetries
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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 Gërxhani, 2008) suggest this is a consequence of the communist experience, which modified social patterns and negatively affected social capital
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- Two indicators: trust and associational life (active participation)
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Empirical methodology

Parametric and nonparametric regressions

- Parametric **(OLS)** regressions

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

- Nonparametric **(kernel)** regressions

$$Y_i = m(Z_i) + \epsilon_i, i = 1, 2, ...n, \tag{2}$$

  - 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
  - Nonparametric regression permits estimating individual effects for every sample point (parameter heterogeneity)
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Nonparametric regression, estimation alternatives

- 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

$$\hat{m}(z) = \frac{\sum_{i=1}^{n} y_i \prod_{s=1}^{q} K\left(\frac{z_{si} - z_s}{h_s}\right)}{\sum_{i=1}^{n} \prod_{s=1}^{q} K\left(\frac{z_{si} - z_s}{h_s}\right)} \tag{3}$$

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

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

  - 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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Nonparametric regression, estimation alternatives

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Outline

Models, sample an data sources

- Sample of 237 European regions (NUTS 2)
- Period of analysis 1995–2007. Two subperiods (1995–2002) and (2003–2007)
- Neoclassical growth equation (Solow, 1957) augmented with social capital
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Descriptive statistics

Sample summary, ECE and non-ECE regions

	1995–2001						2002-2007					
	Non ECE regions			ECE regions			Non ECE regions			ECE regions		
Variable	Obs.	Mean	s.d.	Obs.	Mean	s.d.	Obs.	Mean	s.d.	Obs.	Mean	s.d.
GGDP	190	0.050	0.031	46	0.102	0.031	192	0.036	0.014	46	0.111	0.045
GDP_0	190	17,736	6,995	46	2,892	1,386	192	24,078	8,784	46	5,558	2,867
GPOP	192	0.053	0.005	46	0.048	0.004	192	0.055	0.006	46	0.048	0.003
GFCF	161	0.208	0.055	46	0.218	0.071	156	0.213	0.045	46	0.216	0.052
HC	189	0.214	0.083	46	0.136	0.067	192	0.246	0.081	46	0.170	0.070
TRUST	192	0.334	0.138	46	0.184	0.055	192	0.334	0.138	46	0.184	0.055
ACTIVE	192	0.037	0.022	46	0.022	0.013	192	0.037	0.022	46	0.022	0.013

Outline

Results, parametric regressions

Ordinary least squares (OLS) estimation

Dependent variable: GDP growth (*GGDP*)					
	Model 1	Model 2	Model 3	Model 4	Model 5
(*Intercept*)	0.405***	0.407***	0.419***	0.408***	0.401***
	(0.018)	(0.019)	(0.017)	(0.018)	(0.018)
$log(GDP_0)$	−0.039***	−0.039***	−0.041***	−0.040***	−0.040***
	(0.347)	(0.002)	(0.002)	(0.002)	(0.002)
GPOP	0.216	0.219***	0.073	0.049	0.116
	(0.244)	(0.244)	(0.232)	(0.232)	(0.225)
GFCF	-0.030	-0.031	-0.014	-0.008	-0.026
	(0.028)	(0.028)	(0.027)	(0.027)	(0.026)
HC	0.099***	0.098***	0.091***	0.094***	0.060***
	(0.017)	(0.017)	(0.016)	(0.016)	(0.017)
TRUST		0.003		−0.018*	-0.016
		(0.011)		(0.010)	(0.010)
ACTIVE			0.431***	0.463***	0.504***
			(0.064)	(0.067)	(0.066)
CAPITAL					0.022***
					(0.004)
N	404	404	404	404	404
R^2(*Adjusted*)	0.531	0.530	0.578	0.580	0.616
F_{STAT}	115.20***	91.94***	111.40***	93.69***	72.20***
Time control	No	No	No	No	Yes

Results, parametric regressions

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

	Model 1	Model 2	Model 3	Model 4	Model 5
Jn-statistic	12.828	10.580	5.676	9.820	9.764
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Outline

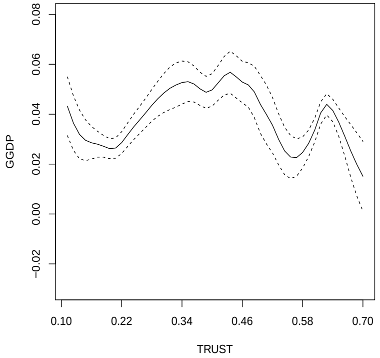
Results, nonparametric regressions

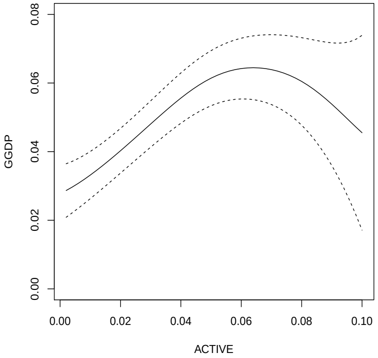
Bandwidths for LCLS and LLLS estimators

Dependent variable: GDP growth (*GGDP*)											
		Model 1		Model 2		Model 3		Model 4		Model 5	
Variables/method	UB	LCLS	LLLS	LCLS	LLLS	LCLS	LLLS	LCLS	LLLS	LCLS	LLLS
$ln(GDP_0)$	1.622	0.134	0.276	0.154	0.205	0.095	0.242	0.1528	0.261	0.287	0.748
GPOP	0.012	0.007	0.008	**1,809**	0.005	0.006	0.007	**22,195**	0.003	0.010	**1,364**
GFCF	0.106	0.016	0.057	**149,738**	0.033	0.016	0.042	**383,800**	0.025	**1,149,916**	0.035
HC	0.173	0.019	0.052	**0.270**	**0.421**	0.033	0.066	**0.269**	0.147	**0.640**	0.075
TRUST	0.278			2.05e-06	0.059			1.16e-04	0.065	0.005	0.029
ACTIVE	0.043					0.007	0.012	0.017	0.027	3.0e-04	0.024
CAPITAL	0.500									0.499	0.007
Time	0.500									0.007	0.024

Results, nonparametric regressions

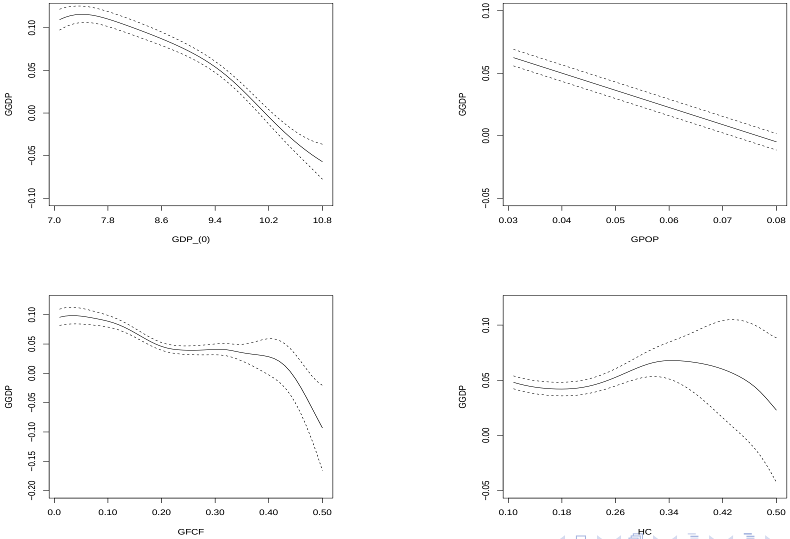
Social capital indicators in Model 5





Results, nonparametric regressions

Control variables in Model 5



Results, nonparametric regressions

LLLS quartile estimates for the continuous regressors

Dependent variable: GDP growth (*GGDP*)									
	Model 1			Model 2			Model 3		
Variables	Q1	Q2	Q3	Q1	Q2	Q3	Q1	Q2	Q3
$ln(GDP_0)$	-0.069	-0.047	-0.030	-0.071	-0.052	-0.040	-0.057	-0.041	-0.023
	(0.006)	(0.003)	(0.003)	(0.003)	(0.008)	(0.006)	(0.005)	(0.003)	(0.002)
GPOP	0.054	0.393	0.719	0.141	0.577	0.973	-0.280	0.116	0.989
	(0.213)	(0.097)	(0.210)	(0.338)	(0.139)	(0.202)	(0.114)	(0.214)	(0.277)
GFCF	-0.216	-0.091	0.025	-0.289	-0.142	0.027	-0.224	-0.065	0.088
	(0.040)	(0.034)	(0.006)	(0.033)	(0.015)	(0.028)	(0.033)	(0.009)	(0.037)
HC	0.020	0.101	0.143	0.035	0.093	0.129	-0.005	0.040	0.117
	(0.035)	(0.017)	(0.041)	(0.018)	(0.026)	(0.024)	(0.010)	(0.048)	(0.025)
TRUST				-0.008	0.033	0.069			
				(0.014)	(0.011)	(0.010)			
ACTIVE							-0.039	0.467	0.744
							(0.127)	(0.163)	(0.224)
N	404			404			404		
R^2	0.816			0.854			0.916		
Time/capital controls	No			No			No		

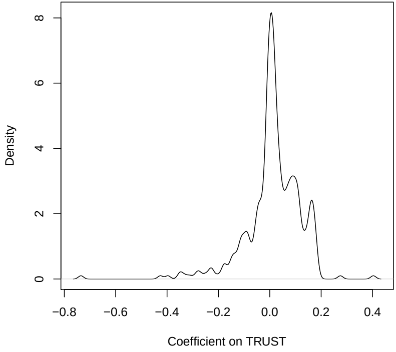
Results, nonparametric regressions

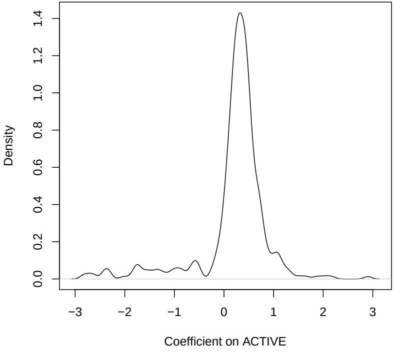
LLLS quartile estimates for the continuous regressors

Dependent variable: GDP growth (*GGDP*)						
	Model 4			Model 5		
Variables	Q1	Q2	Q3	Q1	Q2	Q3
$ln(GDP_0)$	-0.052	-0.034	-0.021	-0.057	-0.035	-0.016
	(0.005)	(0.011)	(0.003)	(0.004)	(0.003)	(0.001)
GPOP	-0.538	0.388	0.921	-0.152	0.168	0.663
	(0.364)	(0.872)	(0.347)	(0.000)	(0.000)	(0.000)
GFCF	-0.276	-0.104	0.08	-0.354	0.024	0.139
	(0.067)	(0.087)	(0.115)	(0.156)	(0.009)	(0.023)
HC	0.000	0.051	0.149	-0.012	0.031	0.099
	(0.012)	(0.005)	(0.017)	(0.012)	(0.003)	(0.011)
TRUST	-0.050	0.024	0.083	-0.018	0.014	0.079
	(0.028)	(0.010)	(0.026)	(0.011)	(0.003)	(0.037)
ACTIVE	0.021	0.373	0.788	0.143	0.322	0.504
	(0.120)	(0.050)	(0.128)	(0.041)	(0.094)	(0.086)
N	404			404		
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)





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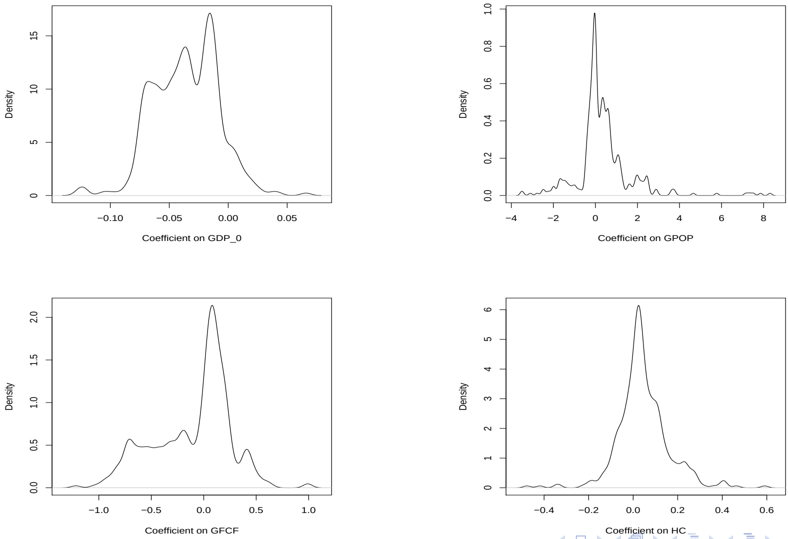


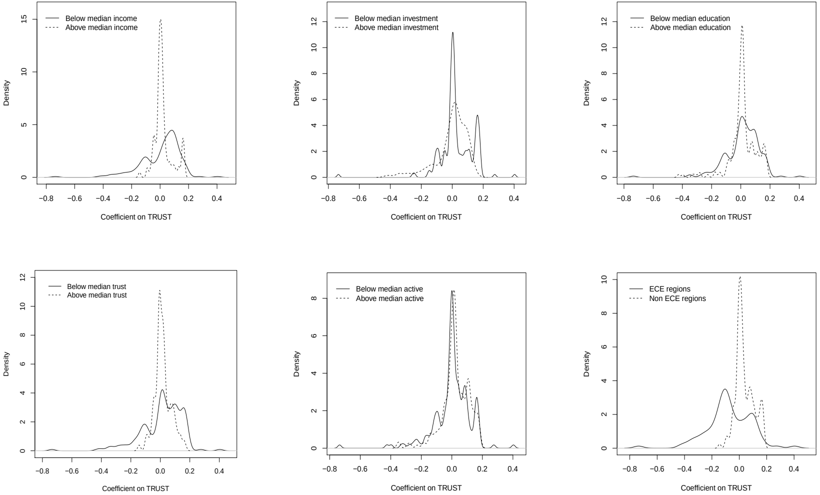
Results, nonparametric regression

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

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

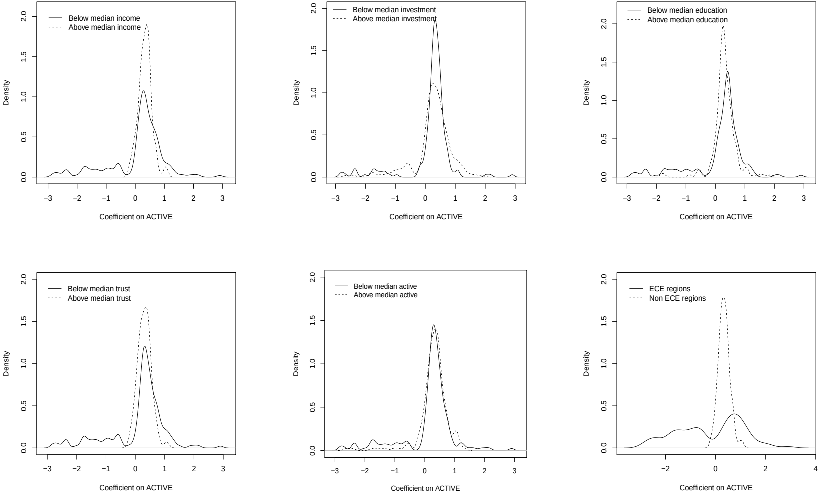
Results, nonparametric regressions

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



Results, nonparametric regressions

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



Results, nonparametric regressions

Nonparametric comparison of the estimated densities for different subgroups in Model 5 (Li, 1996)

		TRUST	*ACTIVE*
Below vs. above GDP_0	t-statistic	46.951	13.288
		(0.000)	(0.000)
Below vs. above *GFCF*	t-statistic	17.757	7.163
		(0.000)	(0.000)
Below vs. above *HC*	t-statistic	12.338	12.150
		(0.000)	(0.000)
Below vs. above *TRUST*	t-statistic	23.646	12.003
		(0.000)	(0.000)
Below vs. above *ACTIVE*	t-statistic	2.768	0.271
		(0.002)	(0.393)
ECE vs. non ECE regions	t-statistic	36.520	59.054
		(0.000)	(0.000)

Results, nonparametric regressions

Dealing with endogeneity

- **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.
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  - **Stage I:** LCLS estimation on the endogenous variables over a set of suitable instruments
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Results, nonparametric regressions
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Dealing with endogeneity

Dependent variable: GDP growth (*GGDP*)											
		Model 1		Model 2		Model 3		Model 4		Model 5	
Variables/method	UB	LCLS	LLLS	LCLS	LLLS	LCLS	LLLS	LCLS	LLLS	LCLS	LLLS
$ln(GDP_0)$	1.622	0.134	0.276	0.154	0.205	0.095	0.242	0.1528	0.261	0.287	0.748
GPOP	0.012	0.007	0.008	**1,809**	0.005	0.006	0.007	**22,195**	0.003	0.010	**1,364**
GFCF	0.106	0.016	0.057	**149,738**	0.033	0.016	0.042	**383,800**	0.025	**1,149,916**	0.035
HC	0.173	0.019	0.052	**0.270**	**0.421**	0.033	0.066	**0.269**	0.147	**0.640**	0.075
TRUST	0.278			2.05e-06	0.059			1.16e-04	0.065	0.005	0.029
ACTIVE	0.043					0.007	0.012	0.017	0.027	3.0e-04	0.024
CAPITAL	0.500									0.499	0.007
Time	0.500									0.007	0.024

Results, nonparametric regressions

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

	Stage I (LCLS)			Stage II (LLLS)	
	UB	D.V: *TRUST*	D.V: *ACTIVE*	UB	D.V: *GGDP*
ln(GDP_0)	1.622	0.111	0.179	1.622	1.181
GPOP	0.012	0.002	0.005	0.012	**1,832.48**
GFCF	0.106	**0.117**	0.017	0.106	0.028
HC	0.173	0.015	0.024	0.173	0.067
TRUST	0.278			0.278	0.071
ACTIVE	0.043			0.043	0.021
CAPITAL	0.500			0.500	0.001
Time	0.500			0.500	0.020
$\hat{\mu}_{TRUST}$				0.147	0.043
$\hat{\mu}_{ACTIVE}$				0.024	0.012

Results, nonparametric regression

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

Dependent variable: GDP growth (*GGDP*)						
	Model 5			IV Model 5		
Variables	Q1	Q2	Q3	Q1	Q2	Q3
$ln(GDP_0)$	-0.057	-0.035	-0.016	-0.050	-0.039	-0.028
	(0.004)	(0.003)	(0.001)	(0.000)	(0.000)	(0.003)
GPOP	-0.152	0.168	0.663	-0.257	0.298	1.221
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GFCF	-0.354	0.024	0.139	-0.288	0.006	0.105
	(0.011)	(0.004)	(0.018)	(0.020)	(0.025)	(0.022)
HC	-0.012	0.031	0.099	-0.048	0.038	0.112
	(0.008)	(0.019)	(0.016)	(0.062)	(0.016)	(0.080)
TRUST	-0.018	0.014	0.079	-0.046	0.034	0.121
	(0.011)	(0.003)	(0.037)	(0.008)	(0.018)	(0.020)
ACTIVE	0.143	0.322	0.504	-0.183	0.298	0.976
	(0.041)	(0.094)	(0.086)	(0.063)	(0.095)	(0.017)
N	404			404		
R^2	0.958			0.980		

Outline

Conclusions

- The linear specification imposed by the parametric methods is not the true underlaying 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
  - Policies should be applied carefully in some regions where they might yield undesired effects

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