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A smooth coefficient quantile regression approach to the social capital–economic growth nexus

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ABSTRACT

This analysis assesses the role of social capital in generating heterogeneity in growth processes across U.S. counties by estimating growth regressions, using the novel semiparametric smooth coefficient quantile regression method in which parameters are unspecified functions of a measure of social capital. The results indicate substantial differences across the quantiles of economic growth in the profile shapes of the coefficient estimates over the level of social capital. Moreover, the coefficient function estimates are highly nonlinear over the level of social capital, providing evidence that the growth process that links initial income, education attainment, ethnic diversity, inequality, population density, and government activity to growth varies with social capital in a nonlinear way.

1. Introduction

Modeling cross-sectional heterogeneity in the growth process is a central issue in economic growth empirics. This paper employs a novel modeling strategy – the smooth coefficient quantile regression (SCQR) model – to examine the role of social capital in generating heterogeneities in the growth process across 3,059 U.S. counties This modeling strategy allows us to model the parameters in growth equations as unspecified quantile-specific smooth functions of the level of social capital and therefore uncovering the hidden structure at various quantiles of the growth distribution.

Ever since Putnam's (1993) influential work which shows that social capital, defined as trust, interpersonal networks, and cooperative norms, is conductive to economic progress, the economic growth literature has witnessed a surge of empirical research on the link between social capital and growth, most of them examine the direct effect of social capital on growth under a parametric conditional mean regression framework.[1] While economic theories have predicted that social capital not only affects growth directly, but also plays a critical role in influencing the environment in which the economy grows, which in turn determines the marginal effects of human capital, government activity, population density, income inequality, and ethnic diversity on economic activities, there has been little evidence on how social capital contributes to heterogeneity in the growth process.[2] In short, the bulk of the extant empirical studies on the social capital–growth nexus adopt a pre-specified parametric mean regression framework and disregard the consequences of imposing linearity and parameter homogeneity and focusing exclusively on the central location of the growth distribution on model interpretability. Assuming linearity and parameter homogeneity may mask complex interactions among the covariates and thereby leading to possible misspecification bias. For instance, constraining the growth

[1] For cross-country or cross-region studies on the association between social capital and growth, see Knack and Keefer (1997), Whiteley (2000), Zak and Knack (2001), Knack (2003), Beugelsdijk et al. (2004), and Beugelsdijk and van Schaik (2005). For three-stage least squares evidence on the transmission channels from social capital to growth, see Bjørnskov (2010).

[2] An exception is Zak and Knack (2001), which finds that the interaction term between social capital and initial GDP to be significantly negative, indicating that more social capital is associated with faster convergence.

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effect of ethnic diversity to be constant or to either increase or decrease monotonically with the level of social capital at a constant rate is unrealistic. It would be more sensible to treat the growth effect of ethnic diversity as a smooth function of the level of social capital.

This paper is closely related to the literature on the heterogeneity of the growth process, which usually involves sorting countries into groups, each having its own distinct growth regime. Using smooth coefficient mean regressions, Durlauf et al. (2001) demonstrate that explicitly accounting for parameter heterogeneity substantially enhances the fit of cross-country growth regression models. Durlauf and Johnson (1995), Canova (2004), Paap et al. (2005), Alfo et al. (2008), Sirimaneetham and Temple (2009), and Owen et al. (2009) respectively use the regression tree analysis, predictive density approach, data-based latent-class panel time series model, non-parametric random coefficient model, threshold regression (Hansen (2000)), and finite-mixture model to group countries and estimate group-specific growth regimes. However, these studies ignore social capital completely and restrict countries in the same group to obey identical growth process.

Another limitation of the extant literature on the social capital–growth nexus is its exclusive focus on the conditional mean of growth. While mean regressions quantify behaviors at the central location of the growth distribution, they provide little information about behaviors at noncentral locations. If the upper or lower quantiles are of interest, then policy implications derived from mean regressions could be misleading.[3] As a concrete example, if the aim is to study the association between social capital and economic growth in slow- (or fast-) growing economies then it is more sensible to model the lower (or higher) percentiles of growth, rather than the conditional mean growth, as the response variable. A way to cope with such problems is to adopt the quantile regression model, which extends the classical mean regression model to a range of models by estimating various conditional quantile functions. It enables one to obtain a more complete picture of how covariate effects differ across the percentiles of the response variable.[4]

This paper extends the smooth coefficient analysis in Durlauf et al. (2001) by fitting a SCQR model for each of the quantiles of the growth distribution of interest. Specifically, we estimate an empirical growth model in which the quantile-specific intercept and marginal effects of initial income, human capital, inequality, ethnic diversity, population density, and government activity on the quantile of the growth distribution of interest are smooth functions of a measure of social capital. The profile shapes of the smooth intercept function and the coefficient functions over the level of social capital will respectively show how a quantile of the growth distribution varies with the level of social capital after conditioning on the covariates and how marginal effects of the covariates are constrained by the level of social capital. Since the SCQR model nests parametric quantile regression models, it tends to fit the data better than the latter model.

Despite the vast literature on growth empirics, there appears to be little confidence in the results, primarily due to the implausible assumption of parameter homogeneity and the exclusive focus on conditional mean.[5] This paper makes four major contributions to the empirical literature on the heterogeneity in cross-sectional growth process. First, it is the first paper to examine the sources of heterogeneous growth by exploring the role of social capital as a conditioning variable that influences the impacts of conventional determinants of growth.[6] Second, in the SCQR framework, economies similar in terms of the position on the conditional growth distribution and levels of social capital have similar but not exactly identical growth processes.[7] Third, this paper complements the existing literature to explore heterogeneity in covariate effects across levels of social capital as well as quantiles of the growth distribution. Fourth, our methodology provides evidence on not only the state variable role, but also the direct information variable role of social capital in the growth process.[8] Unlike linear growth models, where cross-sectional growth differentials are attributed solely to differences in covariate values, the SCQR model attributes cross-sectional differences in economic performance to discrepancies across economies in the value of covariates as well as its marginal effects.

2. Why does social capital matter to economic growth?

This section first surveys the direct effect of social capital on growth and then outlines the theoretic underpinnings for modeling the relationships between human capital, inequality, diversity, government activity and economic growth as functions of a county's level of social capital.

2.1. The direct role of social capital in growth

Social capital is a multidimensional concept. Over the last few decades, scholars from several different disciplines have proposed various definitions for the concept of social capital. From a psychological perspective, Granovetter (1985) points out that people base their economic decisions on past interactions with people and prefer to transact with those who have a good reputation. Hence, economic transactions are embedded within social relationships. Coleman (1988) first terms social capital as "the aspects of social structure that facilitate coordination and cooperation among agents within the structure." In his influential book which popularized the concept of social capital, Putnam (1993) defines social capital as "features of social organization, such as trust, norms, and networks that can improve the efficiency of a society by facilitating coordinated actions." Bowles and Gintis (2002) further refer social capital to "trust, concerns for one's associates, a willingness to live by the norms of one's community and to punish those who do not." Sabatini (2009) distinguishes and builds indicators for five dimensions of social capital: strong family ties, weak informal ties, voluntary organizations, active political participation, and civic awareness. Although a consensus on the definition and measurement of social capital is yet to be reached, the World Bank (2010) offers a broad definition of the notion: "Social capital refers to the norms and networks that enable collective action". It encompasses institutions, relationships, and customs that shape the quality and quantity of a society's social interactions."

The theoretic literature yields contrasting predictions regarding the effect of social capital on growth. Granovetter (1973) argues that weak interpersonal ties facilitate information diffusion, while Olson (1982) posits that horizontal associations tend to represent the interest of a small group of people, leading to inefficient economic policies. Conversely, Putnam (1993) maintains that civic engagement promotes the formation of trust, and thereby improving the quality of governance and thus economic performance. Zak and Knack (2001) propose a model with a moral hazard problem and demonstrate that as more resources are allocated to inspection and monitoring,

[3] For parametric constant-coefficient quantile regression analyses of economic growth, see Barreto and Hughes (2004), Foster (2008), and Ram (2008). These studies, however, do not include social capital as a regressor in their growth equations.

[4] See Koenker (2005) and Hao and Naiman (2007) for excellent introductions and interesting applications of quantile regression.

[5] For reasons why linear growth models are uncompelling and for evidence of parameter heterogeneity across regions, see Durlauf et al. (2001), Brock and Durlauf (2001), and Durlauf et al. (2008).

[6] By contrast, the extant literature focuses on parameter heterogeneity associated with regions, initial income, and institutional quality.

[7] In prior studies that assign countries to growth regimes using threshold regression models or regression tree analysis, economies with a similar level of development are restricted to obey identical growth process. Finite mixture models classify countries into growth regimes according to the combination of class membership predictors, but countries of the same group are still required to operate under identical production regime.

[8] In studies based on finite mixture models, the class membership predictors play the role of state variables that affect the environment in which economic activities take place without influencing growth directly.

the lower the return is to physical capital investment and the rate of investment. Routledge and Amsberg (2003) outline a trading game where gains from trade are a prisoners' dilemma and social structure is a by-product of individuals' rational choice. In their model, social structure determines the frequency of trade, which in turn influences agents' decisions on whether to trade cooperatively. Routledge and Amsberg show that welfare can decrease, increase, or be Pareto-noncomparable after a reduction in social capital. Guiso et al. (2004) demonstrate that higher social trust contributes to higher financial development. Akçomak and ter Weel (2009) present that when social capital is higher, venture capitalists are more willing to invest in innovation.

2.2. The interaction between social capital and human capital

It is well established that human capital is an important determinant of economic performance.[9] Recently, several theoretic analyses postulate that the productivity of human capital is higher in societies having a higher stock of social capital. Burt (1992) analyzes the relationship between strategic positions in networks and compensation and confirms that members in social networks are paid higher. More importantly, Burt finds that due to network externality, some returns from network participation are captured by people who transact with those who invest in social ties, indicating that network externalities may improve the productivity of the economy's aggregate stock of human capital. Dasgupta (2009) further articulates on network externalities in a simple model and concludes that if network externalities are economy-wide, like public goods, then an increase in trust among members of a group of people will manifest itself in total factor productivity (TFP) growth. Knack and Keefer (1997) argue that civic involvements may increase the productivity of human capital for two reasons. First, trust and civic involvement improve the quality of governance, which in turn raises the quality of public-provided education. Second, trust is linked to stronger contract enforcement, which triggers investments in innovation that lead to a higher return to higher education. Papagapitos and Riley (2009) argue that higher trust leads to higher stocks of physical capital, which increases the productivity of human capital. In brief, the aforementioned theories imply that social capital may serve as a conditioning information variable that indicates the quality and productivity of human capital.

2.3. The interaction between social capital and government activity

It has been widely documented that the quality of governance is a key factor behind economic growth.[10] Researchers have even argued that social capital may foster public–private cooperation and help hold accountable the elected representatives. The theoretic literature proposes at least two mechanisms whereby social capital is linked to the quality of governance: the bureaucratic and electoral effects. As for the bureaucratic effect, Arrow (1972) emphasizes that trust and social cohesion leads to an increase in the supply of trustworthy bureaucrats and politicians who make better decisions and implement these decisions effectively. Alternatively, the literature on the electoral effect suggests that politicians are more responsive to voters' demand when citizens are more civically minded. Boix and Posner (1998) and Putnam (2000) claim that social capital makes citizens more sophisticated consumers of politics, who are better able to monitor the government and hold elected politicians accountable for formulating and implementing better policies. Putnam (1993, 2000) demonstrates that in more civic regions, politicians are more likely to compromise and agree with their political opponents. Putnam (1993) also shows that in societies where people are less public-spirited, politics are more likely to be divisive and polarized, rendering innovation and flexibility in policies more difficult.

In sharp contrast, Olson (1982) argues that members of a group may use their connections to lobby for preferential policies such as quotas and restrictions to entry, leading to sclerosis and inefficient policies. Bjørnskov (2010) formally models both the bureaucratic and electoral transmission channels of social capital to the quality of governance. Consistent with the electoral mechanism, Bjørnskov (2010) finds evidence that the effect of trust on governance quality is stronger in countries having a higher degree of political competition. Ahlerup et al. (2009) present a principal–agent investment model and show that social capital has a larger positive effect on economic performance at lower levels of institutional development. However, when institutional strength is sufficiently strong, social capital becomes less growth-enhancing.

Assuming that the underlying culture is a primitive, Carlin et al. (2009) conclude that in societies without (with) complete state contingent contracts and punishment schemes for opportunistic behavior and/or where individuals interact infrequently (frequently), government regulations and trust are substitutes (complements). In this instance, an increase in government regulation results in less (more) aggregate investment and thus decreased (increased) growth. In sum, theories and empirical evidence have established that interpersonal trust yields better governmental performance, which accelerates the process of economic development. From a policy perspective, the next relevant step is to figure out the level of social capital at which the growth effect of government activity is the highest.

2.4. The interaction between social capital and ethnic diversity

The theoretic research on how social polarization shapes economic performance has generated mutually contrasting implications. On the one hand, ethnic diversity may impose costs on economic performance because ethnically diverse communities present more difficulties in agreeing on the management and provision of public goods. On the other hand, diversity in ability and culture may spark creativity and innovation.[11]

Ethnic diversity operates through a variety of channels to dampen economic growth. Keefer and Knack (2002) argue that in polarized societies, government policies protecting property and contractual rights are prone to be unstable, diverting investments toward less risky projects and therefore inhibiting economic growth. Under the assumption that the level of trust is lower in heterogeneous societies, Zak and Knack (2001) propose that agents in more heterogeneous societies spend more resources investigating each other and are more risk-averse, thereby reducing investment and economic growth.[12] In short, diversity reduces the provision of public, worsens the quality of public policies, and draws resources from productive uses towards inspecting and monitoring other ethnic groups. Naturally, the next step inquires into whether a higher stock of social capital can enhance growth

[9] For empirical evidence on the relationship between human capital and growth, see Barro (1991), Mankiw et al. (1992), and Temple (2001).

[10] To name a few, Hall and Jones (1999), Acemoglu et al. (2001), and Acemoglu and Robinson (2006).

[11] Ottaviano and Peri (2006) and Florida (2002a, 2002b) find evidence that diversity has positive amenity effects on rent and wage.

[12] Platteau (1994) provides evidence that heterogeneity in religion and language inhibits trade in West Africa. Knack and Keefer (1997) maintain and provide evidence that social polarization can encourage rent-seeking behavior. Alesina et al. (1999) present evidence showing that agreements regarding school locations are harder to reach in ethnically divided cities.

through promoting communication and cooperation among ethnic groups.[13]

2.5. The interaction between social capital and income inequality

The extant literature postulates that income inequality affects growth primarily through redistributive policies. Alesina and Rodrik (1994) formulate an endogenous growth model with redistributive conflicts among agents and show that inequality leads the median voter to prefer higher taxes. Hence, inequality is harmful for growth because it lowers the economy's investment rate. In a general equilibrium model, Persson and Tabellini (1994) demonstrate that inequality leads to policies that do not protect property rights and do not permit the full private appropriation of the return on investment. Alesina and Perotti (1996) argue that inequality triggers socioeconomic instability, which depresses investments and economic growth. However, in an endogenous growth model where redistribution is in the form of public education, Saint-Paul and Verdier (1993) show that inequality leads to more public education and thus higher economic growth. In another strand of literature that stresses credit market frictions, Bhattacharya (1998) argues that in the presence of credit market imperfections, bequests (while exacerbating inequality) alleviate financial constraints, thereby fostering capital accumulation and economic growth. Notably, Grenier and Wright (2006) argue that in more unequal societies, social networks are more likely to be bonding social capital that connect people who are similar, rather than bridging ties that links people from more heterogeneous groups. The nature and consequences of social networks may change with the extent of inequality in the community. Since associations can play a role in redistributive policies and thereby influence the amount of resources channeled towards the poor, it is of interest to examine when and how social capital improves the growth effect of inequality.[14]

While the aforementioned theoretic works have pointed out that social capital may affect growth through altering the marginal effects of human capital, inequality, government activity, and ethnic diversity on growth, this indirect conditioning information variable role of social capital has been largely untested. Although it seems to be implausible that the effect from a change in, e.g., the level of ethnic diversity index on growth in a community with a higher stock of social capital is the same as that for a community with a lower stock of social capital, most studies in the empirical social capital literature still assume that the parameters of the growth regression are invariant across the level of social capital.[15] In addition, no theoretic work has yet indicated that the social capital and growth determinants interact in the same way in fast- and slow-growing economies. Because covariate effects for economies with little social capital may not be readily translated to those with a higher stock of social capital, and factors identified to explain substantial portions of economic growth in fast-growing economies may not hold the same explanatory powers in slow-growing ones, from the policy perspective it is critical to explicitly account for the potential complex and quantile-dependent interaction between social capital and growth determinants in cross-sectional growth regressions.

[13] Of course, it is also possible that social networks are like enclaves that exacerbate the dampening effect of diversity on growth. In fact, Dasgupta (2009) argues that the more dissimilar the transactors are, the greater the benefits are from transaction, and then enclave-like social networks retard growth.

[14] See Fafchamps (2002, 2004) for evidence on the pros and cons of ethnic-based social networks in increasing access to trade credit.

[15] Durlauf et al. (2001) estimate a Solow growth model in which the aggregate production function and thus the parameters vary according to a country's initial income and they find substantial parameter heterogeneity along that dimension. However, Durlauf et al. (2001) do not consider conditional quantities other than the conditional mean.

3. Method

The bulk of empirical growth literature is based on the following linear regression model.

$$Y_i = \sum_{j=0}^{m} X_{ji}\beta_j + \varepsilon_i, \quad i = 1, 2, \ldots, n, \tag{1}$$

where $X_i = (X_{0i}, X_{1i}, \ldots, X_{mi})$ is an $m+1$ dimensional observation of covariates with its first component being 1, i.e., $X_{0i} = 1$, $\beta = (\beta_0, \beta_1, \ldots, \beta_m)$ is an $(m+1)\times 1$ vector of parameters, and ε_i is the random error. The ordinary least squares (OLS) assume that the conditional mean $E(Y_i|X_i) = \sum_{j=0}^{m} X_{ji}\beta_j$ and that the random error ε_i has conditional mean $E(\varepsilon_i|X_i) = 0$.

When a conditional percentile of Y_i replaces the conditional mean as the response variable in (1), the resultant model is called the parametric quantile regression model. Define the τth conditional quantile as $q_\tau(Y|X) \equiv \inf\{y : F_{Y|X}(y) \geq \tau\}$ and assume that $q_\tau(Y_i|X_i) = \sum_{j=0}^{m} X_{ji}\beta_j^\tau$. The parametric quantile regression is defined as

$$Y_i = \sum_{j=0}^{m} X_{ji}\beta_j^\tau + \varepsilon_i^\tau, \quad i = 1, 2, \ldots, n, \tag{2}$$

where the τth conditional quantile of the error term ε_i^τ is assumed to be zero, i.e. $q_\tau(\varepsilon_i^\tau|X_i) = 0$ (see Koenker 2005). In this setting, $\beta^\tau = (\beta_0^\tau, \beta_1^\tau, \ldots, \beta_m^\tau)$ is a $m+1$ dimensional vector of constant but τ-dependent regression coefficients, where β_0^τ is the intercept term and β_j^τ, $j = 1, 2, \ldots, m$, can be interpreted as the marginal change in the τth conditional quantile of Y associated with a unit change in the jth covariate. Koenker (2005) stresses that compared with OLS, which focus on the conditional mean of the dependent variable, quantile regressions, by focusing locally on a particular point on the conditional distribution, attain a higher robustness and a more natural interpretability. The parametric quantile regression given by Eq. (2) is estimated by choosing β_j^τs to minimize the following loss function:

$$\sum_{i=1}^{n} \rho_\tau\left(Y_i - \sum_{j=0}^{m} X_{ji}\beta_j^\tau\right), \tag{3}$$

where $\rho_\tau(z) = z[\tau - I(z \leq 0)]$ is a V-shaped piecewise linear loss function known as the "check" function and $I(\cdot)$ is the indicator function.

The conventional way to allow covariate effects to vary according to a state variable in a parametric regression is to include interactions terms between the covariates and the state variable. However, parametric models with interaction terms are subject to misspecification, since they restrict the covariate effects to vary with the state variable at a constant rate. For instance, if the effect of ethnic diversity on growth changes nonlinearly with the extent of social connectedness in the community, then a parametric quantile regression model with interaction terms is misspecified.

To accommodate the possible complex interactions between social capital and the determinants of growth, we employ the following semiparametric quantile smooth coefficient model developed by Honda (2004) and Cai and Xu (2009):

$$Y_i = \sum_{j=0}^{m} X_{ji}\beta_j^\tau(U_i) + \varepsilon_i^\tau, \quad i = 1, 2, \ldots, n, \tag{4}$$

where U_i denotes the state variable of the ith observation (X_i, Y_i), ε_i is a random error with τth conditional quantile zero, and the smooth intercept $\beta_0^\tau(\cdot)$ and the smooth coefficients $\beta_1^\tau(\cdot), \ldots, \beta_m^\tau(\cdot)$are now unspecified, but smooth functions of the state variable U. Model (4) implicitly assumes that the conditional quantile $q_\tau\left(Y_i|X_i, U_i\right) = \sum_{j=0}^{m} X_{ji}\beta_j^\tau(U_i)$.

As no economic theories explicitly indicate the functional form of the coefficient function $\beta^\tau(\cdot)$s, to study when and how social capital constraints the growth effects of independent variables, we consider the case that U is a measure of social capital for the ith county. It is important to note that in estimating Eq. (4), we do not include the state variable U (in this analysis, the social capital index) as an independent variable. Nonetheless, the direct relationship between U and the dependent variable is captured by the smooth intercept. An intercept term that does not vary (linearly or nonlinearly) with U is an indication that U is not a direct information variable of Y.

In this paper, we adopt the kernel smoothing method in Cai and Xu (2009) to estimate the $m+1$ coefficient functions. We assume that each coefficient function $\beta_j^\tau(\cdot)$, $j=0, 1, 2,\ldots, m$, has the second derivative. Consequently, by Taylor's theorem, the coefficient $\beta_j^\tau(\cdot)$ can be locally approximated by a linear function in a neighborhood of the given grid point u_0 as follows:

$$\beta_j^\tau(U_i)\approx\beta_j^\tau(u_0)+\beta_j^{\tau(1)}(u_0)(U_i-u_0),$$

where $\beta_j^{\tau(1)}(u_0)=(d\beta_j^\tau(u)/du)|_{\ u=u_0}$, i.e., the first derivative of $\beta_j^\tau(u_0)$ at u_0. We estimate the coefficients functions $\beta_j^\tau(u_0)$s by choosing a_j^τ and b_j^τ, $j=0,\ldots, m$, to minimize the locally weighted loss function given by:

$$\frac{1}{h}\sum_{i=1}^{n}\rho_\tau\left(Y_i-\sum_{j=0}^{m}X_{ji}a_j^\tau-\sum_{j=0}^{m}X_{ji}b_j^\tau(U_i-u_0)\right)\times K\left(\frac{U_i-u_0}{h}\right), \tag{5}$$

where $K(\cdot)$ is the kernel function introduced to assign weights to datapoints in a neighborhood of the grid point u_0; h is the size of the neighborhood known as bandwidth, which controls the smoothness of the estimated coefficient function.[16] Solving the minimization problem in (5) produces the local linear estimate of $\beta_j^\tau(u_0)$. In particular, by Taylor's theorem, $\hat{\beta}_j^\tau(u_0)=\hat{a}_j^\tau$ is taken as the estimates of $\beta_j^\tau(u_0)$. Moving u_0 along the real line generates the entire curve of coefficient estimate $\beta_j^\tau(\cdot)$. The rationale behind the above local linear estimator is straightforward. Simply put, the estimator $\hat{\beta}_j^\tau(u_0)$ is obtained by minimizing the locally weighted loss function given by (5), using the observations $(Y_i, 1, X_{1i},\ldots, X_{mi}, U_i)$ whose U_i are close to u_0.

This paper uses the kth-nearest neighbor (k-nn) rule and the leave-one-out cross validation method (see Abberger, 1998 and Chen et al., forthcoming) to select the optimal bandwidth. As data on social capital index are unevenly distributed in its support, and are particularly sparse at the tails of the distribution, using kernel methods with a constant bandwidth over the whole data range may lead to undersmoothing (oversmoothing) where the data are clustered (sparse). To overcome this problem, in estimating the $\beta_j^\tau(u_0)$s based on Eq. (5), we use varying bandwidth by selecting a fixed number of, say k, observations from those$\{Y_i, X_i, U_i\}_{i=1}^n$with U_i being one of the k nearest neighbors of u_0. According to the *k-nn* technique the bandwidth h used in Eq. (5) is the kth smallest value of $|U_i-u_0|$, $i=1, 2,\ldots, n$.

To perform a statistical inference in the SCQR context, one can use the t-statistics based on the standard errors derived from a consistent estimate of the asymptotic covariance matrix proposed by Cai and Xu (2009). Specifically, Cai and Xu (2009) show that a consistent estimate of the covariance matrix for the vector of coefficient estimates $\hat{\beta}^\tau(u_0)$ can be explicitly expressed as:

$$\hat{\Sigma}(u_0)=\hat{\Omega}_1^{-1}(u_0)\hat{\Omega}_0(u_0)\hat{\Omega}_1^{-1}(u_0), \tag{6}$$

where $\hat{\Omega}_1=\frac{1}{nh}\sum_{i=1}^n w_iX_iX'_iK(U_i-u_0)$and $\hat{\Omega}_0=\frac{1}{nh}\sum_{i=1}^n X_iX'_iK(U_i-u_0)$ with $w_i=I\left(X'_i\hat{\beta}_j^\tau(u_0)-\delta_n<Y_i\le X'_i\hat{\beta}_j^\tau(u_0)+\delta_n\right)/(2\delta_n)$ for any $\delta_n\to 0$ as $n\to\infty$.[17] Consequently, the standard errors of$\hat{\beta}^\tau(u_0)$s are, respectively, estimated by the square root of the diagonal elements of$\hat{\Sigma}(u_0)$.

To compare the overall fit of the parametric model and that of the semiparametric SCQR model, we appeal the goodness of fit measure for quantile regression models introduced by Koenker and Machado (1999). Koenker and Machado's measure is an analog of the R^2 statistic for least squares regression and is referred to as pseudo R^2 in the quantile regression literature.

The goodness of fit measure for quantile regression is defined as

$$R(\tau)=1-V_1(\tau)/V_0(\tau) \tag{7}$$

where $V_0(\tau)=\sum_{i=1}^n\rho_\tau\left(Y_i-\hat{Y}_\tau\right)$, with $\hat{Y}_\tau$ denoting the sample τth -quantile of the response variable, and $V_1(\tau)=\sum_{i=1}^n\rho_\tau(Y_i-\hat{q}_\tau(Y_i|X_i,U_i))$with$\hat{q}_\tau(Y_i|X_i,U_i)$being the model's fitted value computed from either the proposed SCQR model or its parametric counterpart. For example, the fitted value of SCQR model is given by $\hat{q}_\tau\left(Y_i|X_i,U_i\right)=\sum_{j=0}^m X_{ji}\hat{\beta}_j^\tau(U_i)$. By definition, V_1 is the weighted sum of absolute distances between the observed Y_i and the fitted value while V_0 is the weighted sum of absolute distances between the observed Y_is and their sample quantile.

The measure $R(\tau)$ for a fixed value of τ has the same interpretation as the classical R^2 statistic for mean regression models, namely, it ranges between 0 and 1 with a higher value indicating a better fit as a larger share of the sum of the total absolute distances $V_0(\tau)$ is explained by the fitted SCQR model. See also Hao and Naiman (2007) for a detailed discussion of the goodness of fit measure together with an excellent introduction of quantile regression.

The smooth coefficient model for the conditional quantiles has been developed only recently. To the best of our knowledge, no previous work has considered a smooth coefficient model in a quantile setting except Cai and Xu (2009), who use the method to explore how the relationship between quantiles of house prices in the Boston area and the number of rooms in a house varies with educational attainment in the neighborhood. In addition, they also use the SCQR strategy to uncover nonlinearities in the exchange rate of the Japanese Yen against the U.S. dollar.[18] There are, however, a number of applications of the smooth coefficient approach in a mean regression setting — to name a few, Durlauf et al. (2001), Li et al. (2002), Stengos and Zacharias (2006), and Lyssiotou et al. (2008).

4. Empirical model and data

The empirical question investigated in this paper is grounded in the theories outlined in Section 2, which imply that the economy's stock of social capital potentially alters the relationship between economic growth and its determinants. For theτth conditional quantile of the economic growth rate, we consider a regression model of the following form:

$$\begin{aligned}gy_i=\beta_0^\tau(sk_i)+\beta_1^\tau(sk_i)\ln y_i^{1990}+\beta_2^\tau(sk_i)hc_i+\beta_3^\tau(sk_i)dv_i+\beta_4^\tau(sk_i)ie_i\\+\beta_5^\tau(sk_i)fg_i+\beta_6^\tau(sk_i)\lg_i+\beta_7^\tau(sk_i)ld_i+\varepsilon_i\end{aligned} \tag{8}$$

Here, $\ln y_i^{1990}$is the real income per capita in 1990, the dependent variable $gy_i=\frac{1}{10}\left(\ln y_i^{2000}-\ln y_i^{1990}\right)$ is the average annual growth rate over the 10-year period 1990–2000, hc_i denotes the human capital indicator, which is measured by the percent of adult population with a bachelor's degree or higher, dv_i is the ethnic diversity index, ie_i is the Gini index, fg_i is the percent of population employed in the federal government, lg_i is the percent of population employed in state and local governments, ld_i is land area per capita, and the state variable sk_i is a measure of the level of social capital in county i.[19] Although

[16] Throughout this paper, we take $K(z)=(15/16)(1-z^2)^2$ for $|z|\le 1$, and $K(z)=0$ for $|z|>1$.

[17] See Cai and Xu (2009) for details of the estimation of the covariance matrix by Eq. (6) along with two alternative estimation methods for constructing a nonsingular $\hat{\Omega}_1$.

[18] For an excellent introduction to quantile regression, see Koenker (2005). See Chen and Wang (2005) for computational issues of the minimization of the loss function in Eq. (5). Readers interested in the kernel smoothing method are referred to Fan and Gijbels (1996), Wand and Jones (1995), and Simonoff (1996) for excellent introductions.

[19] The speed of convergence$\lambda$is related to$\beta_1$according to the following equation: $\beta_1=(e^{-\lambda T}-1)/T$. The conditional convergence hypothesis is supported if the estimate on β_1 is significantly negative. Here, T is the number of periods used in the calculation of the dependent variable, i.e. the average annual growth, and T equals 10 in this analysis. See page 58 in Barro and Sala-i-Martin (2003) for details on the formula for speed of convergence.

addressing causality in a cross-section can be problematic, the time structure in this analysis provides some indication of a causal relation: the average annual economic growth rate over the period 1990–2000 is correlated with social capital and conventional growth determinants measured in 1990.

Data on U.S. county-level indicators of social capital are drawn from Rupasingha et al. (2006).[20] The comprehensive county-level social capital index (sk) is created using principle component analysis from data on the densities of civic, religious, and sports associations, voter turnout for presidential elections, census response rate, and the number of tax-exempt nonprofit organizations. As Rupasingha et al. (2006) emphasize, the advantages of using county- or state-level indicators of social capital over country-level ones are twofold. First, measurement methods are more homogeneous within rather than across countries, resolving data comparability issues. Second, the main purpose of investment in social capital is to facilitate collective actions, and collective actions are more likely to take place at the subnational level than at the national level.

The ethnic diversity index is constructed using the method proposed by Alesina et al. (1999). Specifically, $dv_i = 1-\sum_i r_i$ where r_i is the share of population self-reported as of race $i \in$(White, Black, Asian, Hispanic, Pacific Islander, American Indian, Other). This diversity index measures the probability that two randomly selected people are from different ethnic groups. As for the measure of income inequality, since the Census Bureau does not provide the Gini index at the county-level, we use the method proposed by Kelly (2000) to construct an estimate of the county-level Gini index.[21] Kelly's method is based on a ratio of mean to median household income.[22] Assume that income follows a log–normal distribution, i.e., $\log(Y) \sim N(\mu_y, \sigma_y^2)$, and then mean income is equal to $\exp\left(\mu_y + \frac{1}{2}\sigma_y^2\right)$, and median income equals $\exp(\mu_y)$. The log of the ratio of mean to median income is $\frac{1}{2}\sigma_y$, which can be used to calculate the Gini coefficient following the formula proposed by Shimizu and Crow (1988): $ie = 2\Phi\left(\frac{\sigma_y}{\sqrt{2}}\right) - 1$, where Φ is the normal distribution. To alleviate the problem of endogeneity, the state variable and the independent variables are all measured in year 1990. Data used in the construction of the dependent and independent variables are drawn from the USA Counties dataset compiled by the U.S. Census Bureau.[23] The analysis includes a total of 3,059 counties. Table 1 presents the descriptive statistics of key variables.

Table 1
Summary statistics.

Variable	Description	Mean	S.D.
gy	Average annual growth rate of real income per capita	0.0134	0.0105
sk	Social capital index	0.0009	1.348
lny^{1990}	Natural logarithm of per capita real income in 1990	4.7378	0.2146
hc	Percent adult population with a bachelor's degree or higher (%)	13.4006	6.4646
dv	Ethnic diversity index	0.176	0.1681
ie	Gini index	0.7392	0.0833
fg	Percent population employed in the federal government	0.0607	0.0459
lg	Percent population employed in the state and local governments	0.132	0.0486
ld	Land area per capita in square miles	0.0965	0.2654

Note: The number of observations is 3059.

5. Empirical results

5.1. OLS and parametric quantile regression results

As a preliminary analysis we estimate OLS and parametric quantile regression models without and with interaction variables between social capital and growth determinants. The inclusion of interaction variables allows the coefficients to vary with the level of social capital at a constant rate.

Table 2 presents the OLS and parametric quantile estimates for the specification without interaction terms. Owing to space limitation, we report only the results for the 0.05th, 0.5th, and 0.95th quantiles. In general, the OLS coefficient estimates have the same sign as their quantile counterparts. Results of both estimation methods confirm conditional convergence across U.S. counties. Moreover, the two methods both indicate that diversity is significantly negatively related to growth, whereas educational attainment and income inequality are significantly positively associated with growth. However, the sign of the OLS estimates on state and local government employment share and the land area per capita differ from their quantile counterpart. While the OLS result indicates that lg is negatively associated with growth, the quantile results show that lg is negatively associated with growth only at the 0.05th and 0.5th quantiles. In contrast, lg is positively associated with growth at the 0.95th quantile. Similarly, ld is negatively related to growth in counties at the 0.05th and 0.5th quantiles and around the mean of the conditional growth distribution, but is positively related to growth at the 0.95th quantile.

Most importantly, the coefficient on sk is positive but insignificant at the 0.05th quantile and significantly negative at the conditional mean and the 0.5th and 0.95th quantiles, implying that social capital is uncorrelated with growth in slow-growing counties, but negatively related to growth in median- and fast-growing counties. These heterogeneities highlight the potential pitfall of deriving policy implications exclusively from classical mean regressions.

We next examine whether the relationships between economic growth and its determinants depend on the level of social capital. The conventional way to introduce parameter heterogeneity into an empirical model is to include interaction terms as additional controls. Table 3 reports the results of this exercise.

Table 2
OLS and parametric quantile regression results: baseline specifications.

	OLS	Parametric quantile regression		
		$\tau = 0.05$	$\tau = 0.5$	$\tau = 0.95$
sk	−0.0006	0.0003	−0.0005	−0.0011
	(2.48)**	(0.70)	(2.83)***	(2.87)***
lny^{1990}	−0.0179	−0.0256	−0.0163	−0.0139
	(8.27)***	(7.73)***	(14.05)***	(4.81)***
hc	0.0005	0.0004	0.0004	0.0006
	(9.35)***	(3.90)***	(11.54)***	(8.53)***
dv	−0.0075	−0.0132	−0.0076	−0.0105
	(5.43)***	(5.03)***	(5.91)***	(3.54)***
ie	0.0104	0.0096	0.0080	0.0027
	(3.43)***	(1.80)*	(3.44)***	(0.44)
fg	−0.0008	−0.0010	−0.0007	−0.0011
	(1.10)	(2.78)***	(2.03)**	(3.06)***
lg	−0.0003	−0.0006	−0.0001	0.0009
	(2.46)**	(8.62)***	(1.31)	(10.38)***
ld	−0.0086	−0.0582	−0.0130	0.0104
	(1.98)**	(72.00)***	(19.13)***	(13.37)***
Constant	0.0860	0.1155	0.0819	0.0840
	(8.57)***	(8.74)***	(16.20)***	(6.92)***
R^2or Pseudo R^2	0.15	0.3202	0.0724	0.0548

Number of observations is 3059.
Absolute values of t statistics are in parentheses.
*Significant at 10%; **significant at 5%; *** significant at 1%.

[20] The U.S. county-level data on social capital 1990–2005 are compiled by Anil Ruphasinga and Stephan J. Goetz. The data are available from the website of the Northeast Regional Center for Rural Development, Penn State University, University Park at http://nercrd.psu.edu/Social_Capital/index.html.

[21] Kelly's method of measuring inequality has been employed by several authors, see, e.g., Brush (2007).

[22] As mean household income is not available from the Census Bureau's data files, following Brush (2007), we construct it by multiplying personal income per capita by average persons per household in the county.

[23] The USA Counties dataset is available at http://censtats.census.gov/usa/usa.shtml.

Table 3
OLS and parametric quantile regression results: specification with interaction terms.

	OLS	Parametric quantile regression		
		$\tau=0.05$	$\tau=0.5$	$\tau=0.95$
sk	0.0084	0.0285	0.0090	0.0082
	(1.36)	(3.16)***	(2.47)**	(0.99)
lny^{1990}	−0.0206	−0.0256	−0.0158	−0.0193
	(8.06)***	(6.55)***	(10.95)***	(4.56)***
hc	0.0005	0.0004	0.0004	0.0007
	(8.96)***	(3.63)***	(11.97)***	(9.38)***
dv	−0.0604	−0.0068	−0.0020	−0.0899
	(1.80)*	(0.18)	(0.09)	(1.31)
ie	0.0106	0.0104	0.0087	0.0042
	(3.23)***	(1.86)*	(4.03)***	(0.82)
fg	−0.0005	0.0015	−0.0008	0.0001
	(0.76)	(4.45)***	(2.50)**	(0.35)
lg	−0.0002	−0.0009	−0.0002	0.0004
	(1.35)	(12.54)***	(3.47)***	(3.51)***
ld	−0.0090	−0.0563	−0.0120	0.0099
	(1.92)*	(68.40)***	(19.28)***	(13.23)***
sk*lny^{1990}	−0.0018	−0.0062	−0.0026	−0.0016
	(1.38)	(2.99)***	(3.12)***	(0.97)
sk*hc	0.0001	0.0001	0.0001	0.0001
	(1.73)*	(1.52)	(3.12)***	(1.70)*
sk*dv	0.0113	−0.0017	−0.0012	0.0170
	(1.56)	(0.21)	(0.26)	(1.15)
sk*ie	−0.0013	0.0000	0.0021	−0.0040
	(0.53)	(0.01)	(1.33)	(1.10)
sk*fg	−0.0009	−0.0011	−0.0005	−0.0027
	(1.99)**	(3.77)***	(1.49)	(11.00)***
sk*lg	−0.0001	0.0004	−0.0001	−0.0005
	(0.87)	(13.52)***	(2.87)***	(10.02)***
sk*ld	0.0008	−0.0008	0.0012	0.0059
	(0.81)	(1.39)	(2.87)***	(12.90)***
Constant	0.0989	0.1154	0.0795	0.1077
	(8.51)***	(7.19)***	(12.30)***	(5.61)***
R^2or Pseudo R^2	0.16	0.3271	0.0755	0.0742

Number of observations is 3059. Absolute values of t statistics are in parentheses.
*Significant at 10%; ** significant at 5%; *** significant at 1%.

The estimation results of the parametric quantile model with interaction terms offer the following insights. First, the interaction term between *sk* and $\ln y^{1990}$enters significantly negatively at the 0.05th and 0.5th quantiles, indicating that social capital accelerates income convergence only in low- and median-growth counties. Second, the coefficient on the interaction term between *sk* and *hc* is positive and significant at the 0.5th and 0.95th quantiles, suggesting that in median and high-growth counties one can boost the productivity of human capital by promoting social capital formation. However, policies aimed at making human capital more productive through increasing social capital may be ineffective in slow-growing counties. Third, the coefficient on the interaction between *sk* and *fg* is significantly negative at the 0.05th and 0.95th quantiles, suggesting that in low- and high-growth counties promoting social capital formation worsens the growth impact of government employment at the federal level. Fourth, the interaction term between *sk* and *lg* enters positively (negatively) and significantly at the 0.05th (0.5th and 0.95th) quantile, indicating that accumulating social capital can make state and local governments more (less) growth-enhancing in low- (median and high-) growth counties. Fifth, the coefficient on the interaction term between *sk* and *ld* is significantly positive at the 0.5th and 0.95th quantiles. Therefore, promoting social networks and enhancing social embeddedness in median and high-growth counties make declines in population density less detrimental to growth.

In sum, the signs and magnitudes of the coefficient estimates differ across the quantiles of economic growth rate. Thus, growth-enhancing policies derived from mean regressions may not have the desired effect in counties at the tails of the growth distribution. The finding of parameter heterogeneity across points on the conditional growth distribution illustrates potential information gains from the estimation of the entire conditional distribution of growth as opposed to the conditional mean only. Moreover, there is evidence that the convergence speed and marginal effects of human capital, government activity, and population density on growth vary with the level of social capital at a constant rate.

5.2. Smooth coefficient quantile regression results

As mentioned, the major limitation of the parametric model with interaction terms is that the covariate effects are constrained to vary with social capital at a constant rate. To allow the covariate effects to vary with the level of social capital in a more flexible way, we apply the novel semiparametric smooth coefficient quantile estimation strategy developed by Cai and Xu (2009) to estimate growth equations. The cross-validated optimal number of observations included in the local linear *k-nn* estimation, which controls the amount of local information used to construct the estimates, is $k_{opt}=592$ for $\tau=0.05$, 426 for $\tau=0.5$, and 568 for $\tau=0.95$.

To illustrate the extent of heterogeneity and to identify the level of social capital index at which each covariate has the largest impact on growth, we list in Table 4 the minimum and maximum statistically significant estimates of $\beta_j^{\tau}(sk)$, $j=0,\ 1,\ldots,\ 7$ for the quantiles $\tau=0.05$,0.5, and 0.95 together with the corresponding level of social capital index. The disparities between the minimum and maximum of coefficient estimates are large in magnitude, providing evidence that cross-county differences in the social structure in which economic activities take place may lead to heterogeneities in the way lny^{1990}, *hc, dv, ie, fg, lg*, and *ld* affect growth. For example, at $\tau=0.5$ the implied convergence rate ranges from 0.7% (when *sk* equals 0.6047) to 9.17% (when *sk* equals 2.3079). At $\tau=0.05$, when *sk* is equal to −0.5681, an increase in the Gini index by 0.01 is associated with a 0.0116 percentage point decrease in the 0.05th percentile of economic growth rate. In contrast, when *sk* is equal to −3.5327, the same increase in the Gini index is associated with a 0.117 percentage point increase in the 0.05th percentile of growth.

It can also be seen from Table 4 that the covariate effects can vary substantially depending on the county's position on the growth distribution. For instance, the last column in Table 4 shows that for the county at the 0.05th growth quantile with a social capital index of −3.5327, an increase in land area per capita by 0.01 square miles is associated with an increase in growth of 0.062 percentage point. In contrast, in a county with the same amount of *sk* but is located at the 95th quantile, the same increase in *ld* is associated with a 0.0631 percentage point fall in growth.

The complete picture of parameter heterogeneity can be visualized using a three dimensional plot. As an illustration, Fig. 1 plots the estimated coefficient of land area per capita against the social capital index and quantiles ($\tau=0.1$, 0.3, 0.5, 0.7, 0.9) on two horizontal axes. One can observe from Fig. 1 that for all values of τ, the coefficient estimate on *ld* is highly nonlinear over *sk* and that different percentiles of growth exhibit different patterns of social capital–economic growth nexus.

Figs. 2 through 9 respectively plot the estimated coefficient functions $\beta_j^{\tau}(sk), j=0,1,\ldots,7$(red solid line) and their 90% pointwise confidence intervals (dashed lines) against *sk* for three quantiles $\tau=0.05$,0.5, and 0.95. To contrast our results with those obtained using conventional methods, we also plot the marginal effects obtained from the parametric quantile model with interaction terms (blue solid line).[24]

As seen from these diagrams, in most cases the coefficient estimates from the parametric model with interaction terms are outside the 90% confidence bounds of the smooth coefficient model over a wide range of the level of *sk*.[25] Since the SCQR model nests the

[24] The estimates from a parametric quantile regression model with interaction terms are detailed in Table 3.

[25] The exceptions are the parametric coefficient estimates on *hc* and *fg* at the 0.05th quantile, which lie entirely within the 90% confidence bounds of the corresponding coefficient estimate.

Table 4
Minimum and maximum of significant coefficient estimates and convergence speed.

		Convergence speed	intercept	hc	dv	fg	lg	ie	ld
$\tau=0.05$	Max	0.0649	0.1759	0.0011	−0.0328	0.0084	NA	0.1177	0.0620
		[−3.5327]	[1.5639]	[2.1675]	[3.963]	[−3.062]		[−3.5327]	[−3.5327]
	Min	0.0098	0.0328	0.0002	−0.0376	−0.0247	NA	−0.0116	−0.0850
		[−0.0158]	[−0.0151]	[−0.8437]	[1.8616]	[0.6440]		[−0.5681]	[0.3016]
$\tau=0.5$	Max	0.0917	0.2809	0.0012	−0.0039	−0.0080	0.0040	0.0255	−0.0043
		[2.3079]	[2.3079]	[2.4364]	[−0.9213]	[2.8052]	[0.1425]	[1.7704]	[−1.1321]
	Min	0.007	0.0327	0.0001	−0.0198	−0.0310	−0.0017	−0.0502	−0.0464
		[0.6047]	[0.0952]	[−1.8510]	[−2.9226]	[−3.5327]	[−0.7154]	[3.3339]	[−3.5327]
$\tau=0.95$	Max	0.0483	0.1936	0.0039	−0.0032	0.0204	NA	0.0294	0.0239
		[2.2318]	[2.2038]	[−3.5327]	[−0.1417]	[−2.3865]		[0.0528]	[0.3627]
	Min	0.0072	0.0384	0.0002	−0.0479	−0.0480	NA	−0.0353	−0.0631
		[−0.1407]	[−0.2928]	[−0.2523]	[3.9416]	[−3.5327]		[3.5905]	[−3.5327]

The maximums and minimums are based on estimates that are significant at the 10 percent level.
The levels of social capital at which the maximum/minimum occur are in the square brackets.
NA indicates that the coefficient is statistically insignificant at the 10 percent level at all values of social capital.

parametric model, this finding indicates that the parametric model with interaction terms is misspecified and restricting the covariate effects to change with *sk* at a constant rate is likely to generate misleading results. Moreover, for most covariates the profile shape of the estimated coefficient function over the level of social capital differs substantially across the three quantiles, demonstrating that the conditioning variable role of social capital differs widely across fast- and slow-growing economies. This behavior is difficult to model using a parametric specification in a mean regression setting.

A number of conclusions can be drawn from the results in Figs. 2–9. Fig. 2 shows that the smooth intercept varies with *sk* in a highly nonlinear fashion. Recall that the pattern of the intercept term signifies the direct information variable role of social capital. Irrespective of the quantile, the intercept from the benchmark parametric model is outside the 90% confidence bands of the SCQR model for a large share of *sk*, suggesting that ceteris paribus, social capital affects growth directly but nonlinearly.

Fig. 3 shows that for all three quantiles, the coefficient on initial income is statistically significantly negative over most of the range of *sk*, supporting the hypothesis of conditional convergence. The statistically significant estimates on lny^{1990} imply that for slow-growing counties, convergence rate is highest when social capital is scarce, whereas for counties at the median of the growth distribution, convergence rate is highest when social capital is highly developed. Therefore, accelerating convergence through cultivating social capital is effective (counterproductive) in counties with median (low) economic growth rate.

We now turn to the coefficient estimate on educational attainment in Fig. 4. For all three quantiles considered, educational attainment is statistically significantly positively associated with growth over most of the range of *sk*, suggesting that human capital is good for growth. Note that at $\tau=0.05$(0.5 and 0.95), the coefficient from the parametric model with interaction terms is inside (outside) the 90% confidence bounds for most values of *sk*, indicating that the growth effect of human capital increases linearly (nonlinearly) with the level of social capital. For low-growth counties, educational attainment exerts a more pronounced impact on growth when *sk* is higher. For median-growth counties, the growth impact of educational attainment is most pronounced when *sk* is either very low or very high. In contrast, for high-growth counties human capital is most growth-enhancing at low levels of *sk*. These results together imply that boosting the productivity of human capital through social capital formation is viable only in low- and median-growth counties.

Fig. 5 plots the estimated coefficient function for ethnic diversity. For all three quantiles considered and over most of the range of *sk*, the coefficient on *dv* is statistically significantly negative. This suggests that diversity is generally bad for growth. The coefficient estimate varies widely across the quantiles and does not exhibit any sort of monotonicity over *sk*. It is noteworthy that at the 0.05th quantile, the coefficient on diversity turns significantly positive at high values of *sk*, suggesting that diversity can actually be turned into an advantage in slow-growing counties by maintaining a high level of social capital. However, doing so is likely to aggravate the adverse effect of diversity on growth in fast-growing counties.

One can observe from Fig. 6 that for all quantiles, the coefficient estimate on inequality is significantly negative at high values of *sk*, indicating that inequality is more detrimental to growth where social capital is more developed. This finding is important, as it constitutes evidence that social networks may act as special interest groups that channel resources towards the rich.

Fig. 7 graphs the estimated coefficient function of federal government size. Irrespective of the quantile, the coefficient on *fg* is insignificantly different from zero over most of the range of *sk*. However, at $\tau=0.05$, *fg* has statistically significantly positive effects on growth when social capital is scarce. On the other hand, at $\tau=0.5$ and 0.95, the coefficient function on *fg* follows an inverted U shape with the coefficient estimates on *fg* negative and significant at very low and very high values of *sk*. The implication of these results is that, while federal government activities are positively correlated with growth in slow-growing counties with little social capital, they are particularly bad for growth in median- and high-growth counties that have very high or very low levels of social capital.

Fig. 8 illustrates that regardless of the quantile, the coefficient on state and local government size is insignificant and small in magnitude over most of the range of *sk*. This leads us to conclude that the growth effect of state and local government activity is largely insignificant and modest.

Fig. 9 illustrates interesting differences across the conditional growth quantiles in the profile shapes of the coefficient estimates on land area per capita over the range of the social capital index. At $\tau=0.05$, the coefficient function on *ld* is significantly positive (negative) at low (medium and high) values of *sk*, indicating that population density exerts a negative (positive) impact on growth in slow-growing counties with little (much) social capital. It is therefore possible to make population density more growth-enhancing by building social capital in slow-growing counties that are short of social capital. At $\tau=0.5$, the coefficient estimate on *ld* is significantly negative throughout the range of *sk*, indicating that population density is good for growth in median-growth counties and is particularly so when social capital is scarce. At $\tau=0.95$, the coefficient function of *ld* is largely an increasing function of *sk*. While the coefficient estimate on *ld* is significantly negative at low values of *sk*, it turns significantly positive at high values of *sk*. These results imply that population density is good (bad) for growth at high-growth counties that are short of (abundant in) social capital. Thus, nurturing social capital in median- and high-growth counties with little social capital will

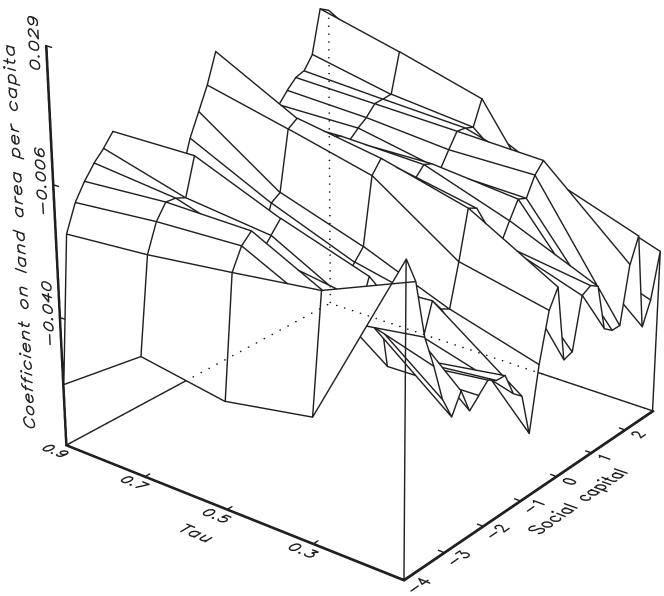

Fig. 1. Estimated coefficient on land area per capita at various quantiles and levels of social capital.

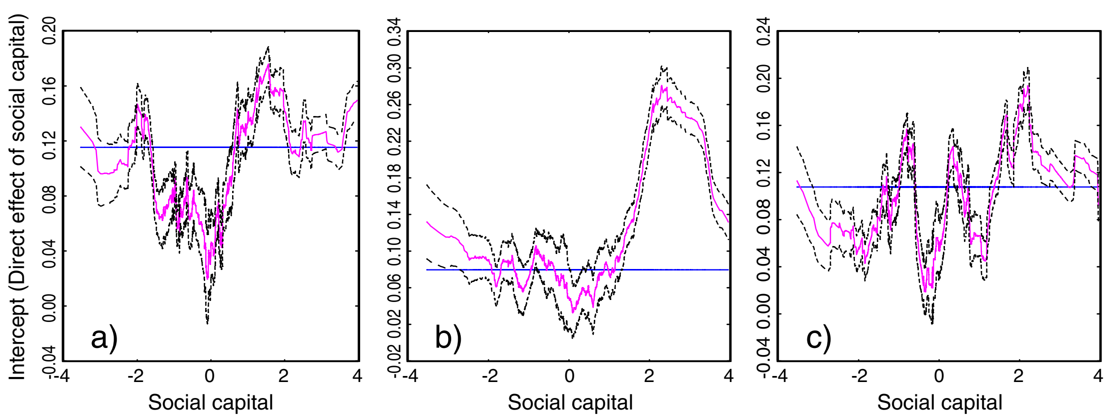

Fig. 2. Smooth intercept estimates. Note: The red, blue, and dashed lines indicate the estimated coefficient function of the semiparametric smooth coefficient model, the estimates from the parametric model with interaction terms between the social capital index and the covariates, and the 90% confidence bounds for the semiparametric model, respectively. Please see Table 3 for the coefficient estimates of the parametric quantile regression model with interaction terms.

likely make population density less growth-enhancing or even growth-impeding.

Finally, to compare the goodness of fit of our semiparametric SCQR model and that of the parametric quantile regression model with interaction terms, we plot in Fig. 10 the $R(\tau)$ (pseudo R^2) for both models against τ.[26] Two implications can be drawn from Fig. 10. First and most importantly, irrespective of the percentile, the pseudo R^2 for the SCQR model is always about 0.1 higher than that for the parametric model, confirming that the SCQR model fits the data better. Second, both models fit the data better at lower tails. For both models the pseudo R^2 is highest at $\tau=0.05$. At $\tau=0.05$, the covariates in the smooth coefficient (parametric) model explains 43.88% (32.87%) of the variation in the 0.05th percentile of economic growth. The goodness of fit for the SCQR model (parametric model with interaction term) deteriorates monotonically as τ increases and reaches its minimum of 0.1053 (0.0461) at $\tau=0.7$ (0.9). These results imply that the covariates explain a greater proportion of observed economic growth in slow-growing counties than in median- and fast-growing counties.

6. Conclusions

In contrast to earlier empirical literature on multiple growth regimes which focused on heterogeneity over income level, this study delves deeper into the source of heterogeneous growth by focusing on the role of a more meaningful variable – social capital – in generating parameter heterogeneity. Based on a cross-sectional county-level data set from the U.S., this analysis addresses modeling issues that may have limited the scope of heterogeneity found in earlier research, such as the sorting of countries into groups, the restriction that requires a single growth regime applies to all countries in the same grouping, the ex ante restrictions on the functional forms, and the failure to provide evidence on differences in the interactions between social capital and growth determinants across quantiles of the growth distribution.

[26] Formula (7) is a measure of the goodness of fit for a given τ. Hao and Naiman (2007) suggest that the assessment of the goodness of fit of a smooth coefficient quantile regression model for the whole distribution requires examining $R(\tau)$ collectively. Following their suggestion, we calculate $R(\tau)$ for $\tau=0.05$, 0.1, 0.2,…, 0.9, 0.95.

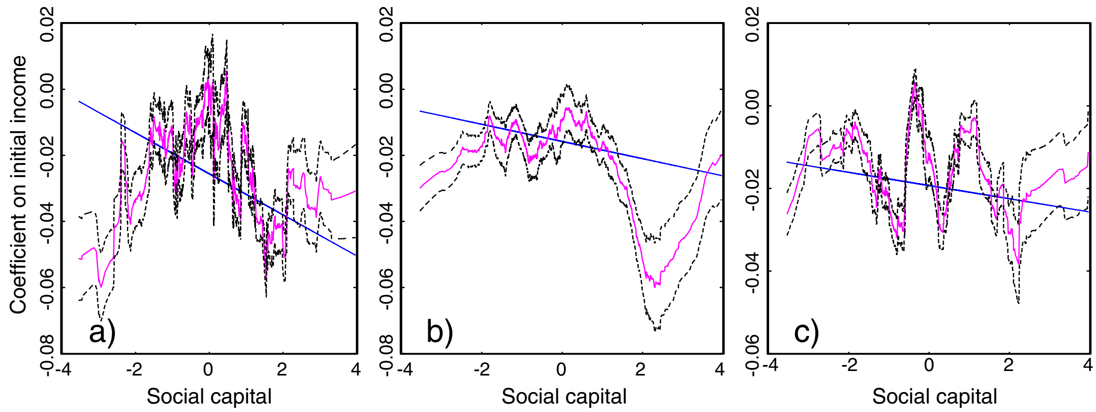

Fig. 3. Smooth coefficient function estimates for initial income. Note: The red, blue, and dashed lines indicate the estimated coefficient function of the semiparametric smooth coefficient model, the estimates from the parametric model with interaction terms between the social capital index and the covariates, and the 90% confidence bounds for the semiparametric model, respectively. Please see Table 3 for the coefficient estimates of the parametric quantile regression model with interaction terms.

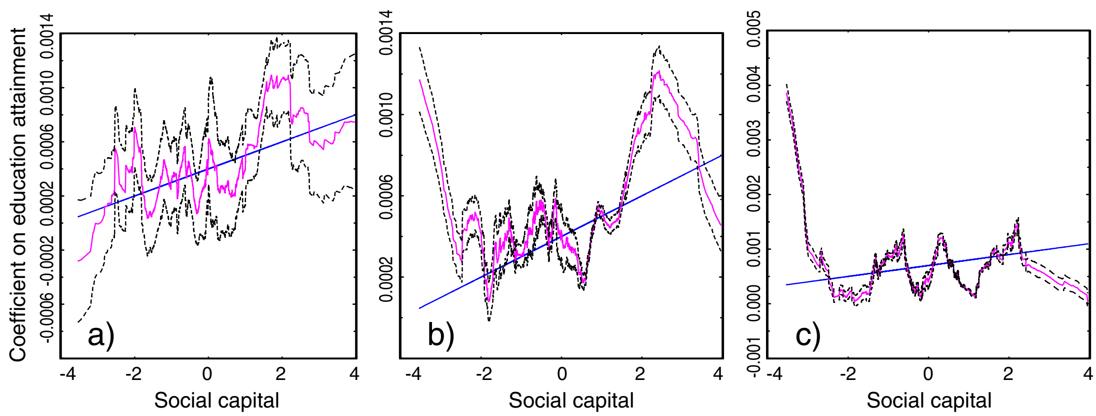

Fig. 4. Smooth coefficient function estimates for education attainment. Note: The red, blue, and dashed lines indicate the estimated coefficient function of the semiparametric smooth coefficient model, the estimates from the parametric model with interaction terms between the social capital index and the covariates, and the 90% confidence bounds for the semiparametric model, respectively. Please see Table 3 for the coefficient estimates of the parametric quantile regression model with interaction terms.

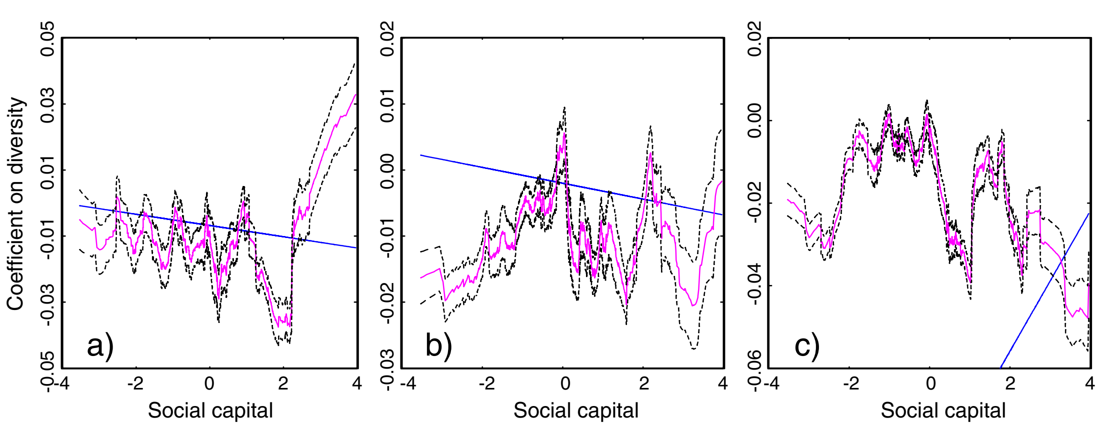

Fig. 5. Smooth coefficient function estimates for ethnic diversity. Note: The red, blue, and dashed lines indicate the estimated coefficient function of the semiparametric smooth coefficient model, the estimates from the parametric model with interaction terms between the social capital index and the covariates, and the 90% confidence bounds for the semiparametric model, respectively. Please see Table 3 for the coefficient estimates of the parametric quantile regression model with interaction terms.

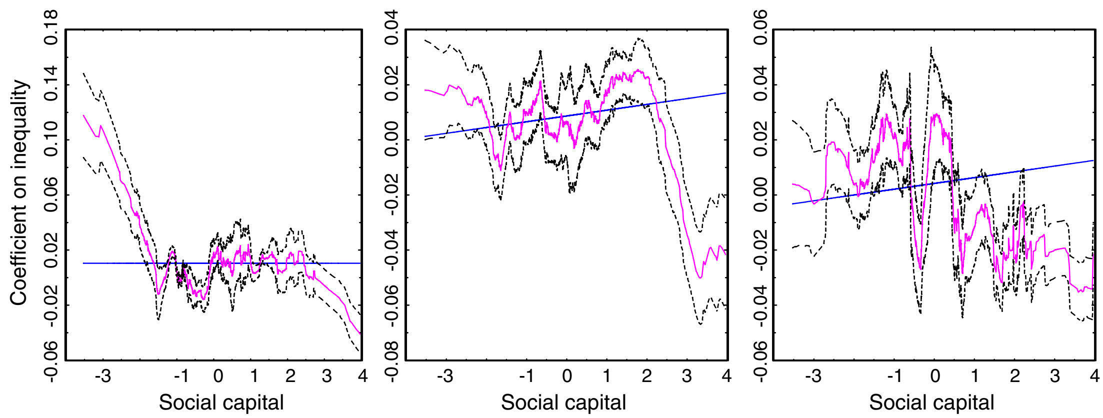

Fig. 6. Smooth coefficient function estimates for income inequality. Note: The red, blue, and dashed lines indicate the estimated coefficient function of the semiparametric smooth coefficient model, the estimates from the parametric model with interaction terms between the social capital index and the covariates, and the 90% confidence bounds for the semiparametric model, respectively. Please see Table 3 for the coefficient estimates of the parametric quantile regression model with interaction terms.

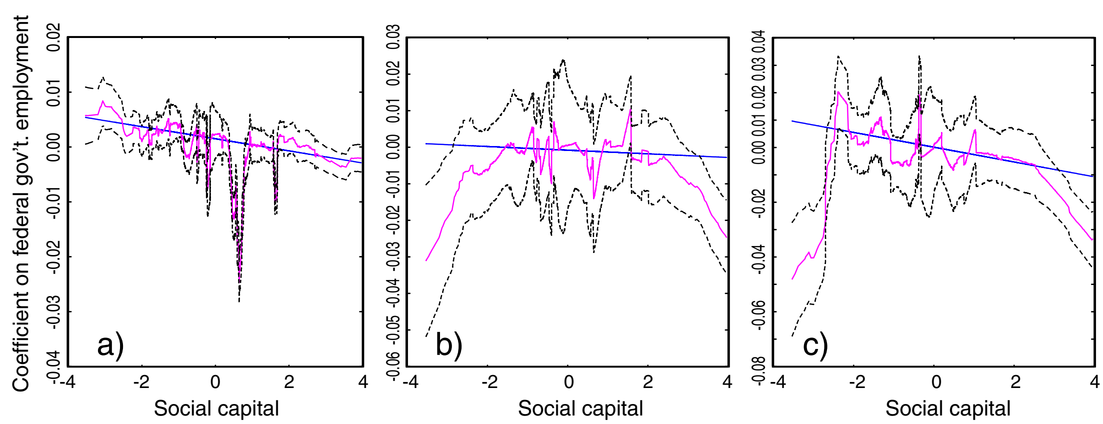

Fig. 7. Smooth coefficient function estimates for federal government employment share. Note: The red, blue, and dashed lines indicate the estimated coefficient function of the semiparametric smooth coefficient model, the estimates from the parametric model with interaction terms between the social capital index and the covariates, and the 90% confidence bounds for the semiparametric model, respectively. Please see Table 3 for the coefficient estimates of the parametric quantile regression model with interaction terms.

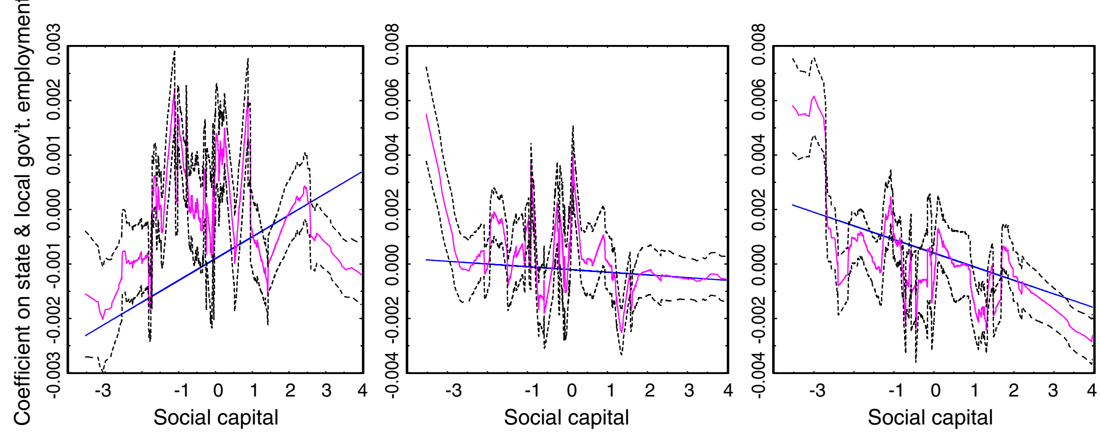

Fig. 8. Smooth coefficient function estimates for state and local government share. Note: The red, blue, and dashed lines indicate the estimated coefficient function of the semiparametric smooth coefficient model, the estimates from the parametric model with interaction terms between the social capital index and the covariates, and the 90% confidence bounds for the semiparametric model, respectively. Please see Table 3 for the coefficient estimates of the parametric quantile regression model with interaction terms.

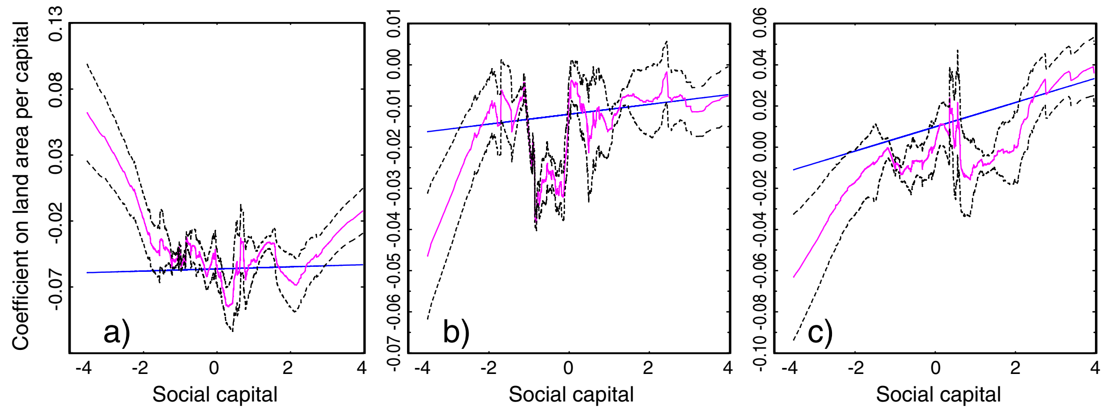

Fig. 9. Smooth coefficient function estimates for land area per capita. Note: The red, blue, and dashed lines indicate the estimated coefficient function of the semiparametric smooth coefficient model, the estimates from the parametric model with interaction terms between the social capital index and the covariates, and the 90% confidence bounds for the semiparametric model, respectively. Please see Table 3 for the coefficient estimates of the parametric quantile regression model with interaction terms.

To examine the role of social capital in generating parameter heterogeneity in the growth process, we estimate cross-county growth equations using Cai and Xu's (2009) smooth coefficient quantile regression method. This modeling approach permits both the direct effect of social capital on growth and the marginal effects of conventional growth determinants on growth to vary nonlinearly with the level of social capital and allows the pattern of this variation to differ across the quantiles of the growth distribution. The pseudo R^2s confirm that the goodness of fit of the SCQR model is higher than that of the benchmark parametric model at all quantiles of the growth distribution.

The main findings are as follows. First, the percentiles of growth exhibit substantially different profile shapes of the estimated coefficient functions. Second, there is evidence of strong heterogeneity in the marginal effects of initial income, human capital, income inequality, ethnic diversity, government activity, and population density on the percentiles of growth over the level of social capital. Third, since the SCQR model permits nonlinear interactions between the covariates and social capital, it is found to fit the data better than a benchmark parametric model.

Our results imply that cross-sectional variations in economic performances stem from not only differences in the values of growth determinants, but also differences in the impacts these variables generate, which in turn depend on the economy's level of social capital and position on the growth distribution. The highly nonlinear and in many cases non-monotonic coefficient function estimates indicate that the role of social capital in determining the growth regime is complex. As such, parametric mean regression models that ignore heterogeneity and nonlinearity in the growth process may yield misleading conclusions for a wide range of counties.

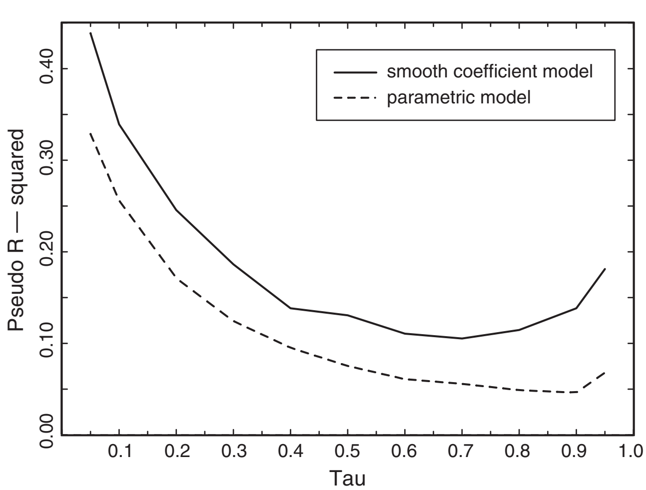

Fig. 10. Goodness of fit measures for the smooth coefficient quantile regression model and the parametric quantile regression model with interaction term.

More research is needed to understand the interaction between social capital and growth determinants more completely. A given type of social capital that is growth-enhancing in some cases may hamper growth in others. An interesting extension to our work is to re-estimate growth regressions using measures of different dimensions of social capital as a state variable, such as voter turnout, degree of social trust, and densities of various types of social networks.

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References

Abberger, K., 1998. Cross-validation in nonparametric parametric quantile regression. Allgemeines Statistisches Archiv 82 (2), 149–161.
Acemoglu, D., Robinson, J., 2006. De facto political power and institutional persistence. American Economic Association Papers and Proceedings 96 (2), 325–330.
Acemoglu, D., Johnson, S., Robinson, J., 2001. The colonial origins of comparative development: an empirical investigation. American Economic Review 91, 1369–1401.
Ahlerup, P., Olsson, O., Yanagizawa, D., 2009. Social capital vs institutions in the growth process. European Journal of Political Economy 25, 1–14.
Akçomak, I., ter Weel, B., 2009. Social capital, innovation and growth: evidence from Europe. European Economic Review 53 (5), 544–567.
Alesina, A., Perotti, R., 1996. Income distribution, political instability, and investment. European Economic Review 40 (6), 1203–1228.
Alesina, A., Rodrik, D., 1994. Distributive politics and economic growth. Quarterly Journal of Economics 109 (2), 465–490.
Alesina, A., Baqir, R., Easterly, W., 1999. Public goods and ethnic divisions. Quarterly Journal of Economics 114 (4), 1243–1284.
Alfo, M., Giovanni, T., Robert, J.W., 2008. Testing for country growth heterogeneities in growth models using a finite mixture approach. Journal of Applied Econometrics 23, 487–514.
Arrow, K., 1972. Gifts and exchanges. Philosophy and Public Affairs 1 (4), 343–362.
Barreto, P., Hughes, A., 2004. Under performers and over achievers: a quantile regression analysis of growth. The Economic Record 80, 17–35.
Barro, R., 1991. Economic growth in a cross section of countries. Quarterly Journal of Economics 106 (2), 407–443.
Barro, R., Sala-i-Martin, X., 2003. Economic Growth, 2nd Edition. MIT Press, Cambridge.
Beugelsdijk, S., van Schaik, A., 2005. Social capital and growth in European regions: an empirical test. European Journal of Political Economy 21 (2), 301–324.
Beugelsdijk, S., de Groot, H., van Schaik, A., 2004. Trust and economic growth: a robustness analysis. Oxford Economic Papers 56, 118–134.
Bhattacharya, P.C., 1998. Migration, employment and development: a three-sector analysis. Journal of International Development 10, 899–921.
Bjørnskov, C., 2010. How does social trust lead to better governance? An attempt to separate electoral and bureaucratic mechanisms. Public Choice 144 (1), 323–346.

Boix, C., Posner, D., 1998. Social capital: explaining its origins and effects on government performance. British Journal of Political Science 28 (4), 686–693.

Bowles, S., Gintis, H., 2002. Social capital and community governance. The Economic Journal 112, 419–436.

Brock, W., Durlauf, S., 2001. Growth empirics and reality. World Bank Economic Review 15 (2), 229–272.

Brush, J., 2007. Does income inequality lead to more crime? A comparison of cross-sectional and time-series analyses of United States counties. Economics Letters 96 (2), 264–268.

Burt, R., 1992. Structural holes: The social structure of competition. Harvard University Press, Cambridge, Massachusetts.

Cai, Z., Xu, X., 2009. Nonparametric quantile estimations for dynamic smooth coefficient models. Journal of the American Statistical Association 104 (485), 371–383.

Canova, F., 2004. Testing for convergence clubs in income per capita: a predicted density approach. International Economic Review 45 (1), 49–77.

Carlin, B., Dorobantu, F., Viswanathan, S., 2009. Public trust, the law, and financial investment. Journal of Financial Economics 92 (3), 321–341.

Chen, C., Wang, Y., 2005. Computational issues for quantile regressions. The Indian Journal of Statistics 67 (2), 399–417.

Chen, Y.J., Deng, W.S., Yang, C.C., Matthews, S., forthcoming. Geographically weighted quantile regression (GWQR): An Application to US Mortality Data. Geographical Analysis.

Coleman, J., 1988. Social capital in the creation of human capital. The American Journal of Sociology 94, S95–S120.

Dasgupta, P., 2009. Matter of trust: social capital and economic development, unpublished paper presented at the Annual Bank Conference on Development Economics (ABCDE), Seoul.

Durlauf, S., Johnson, P., 1995. Multiple regimes and cross-country growth behavior. Journal of Applied Econometrics 10 (4), 365–384.

Durlauf, S., Kourtellos, A., Minkin, A., 2001. The local Solow growth model. European Economic Review 45 (4–6), 928–940.

Durlauf, S., Kourtellos, A., Tan, C.M., 2008. Are any growth theories robust ? The Economic Journal 118, 329–346.

Fafchamps, M., 2002. Returns to social network capital among traders. Oxford Economic Papers 54 (2), 173–206.

Fafchamps, M., 2004. Market institutions in Sub-Saharan Africa. MIT Press, Cambridge.

Fan, J., Gijbels, I., 1996. Local Polynomial Modelling and its Applications. Chapman and Hall, London.

Florida, R., 2002. The rise of the creative class. Basic Books, New York.

Foster, N., 2008. The impact of trade liberalization on economic growth: evidence from a quantile regression analysis. Kyklos 61 (4), 543–567.

Granovetter, M., 1973. The strength of weak ties. The American Journal of Sociology 78 (6), 1360–1380.

Granovetter, M., 1985. Economic action and social structure: the problem of embeddedness. The American Journal of Sociology 91, 481–493.

Grenier, P., Wright, K., 2006. Social capital in Britain: exploring the Hall paradox. Policy Studies 27 (1), 27–53.

Guiso, L., Sapienza, P., Zingales, L., 2004. The role of social capital in financial development. American Economic Review 94 (3), 526–556.

Hall, R., Jones, C., 1999. Why do some countries produce so much more output per worker than others? Quarterly Journal of Economics 114 (1), 83–116.

Hansen, B., 2000. Sample splitting and threshold estimation. Econometrica 68 (3), 575–603.

Hao, L., Naiman, D.Q., 2007. Quantile Regression. Sage Publications, Thousand Oaks, California.

Honda, T., 2004. Quantile regression in varying coefficient models. Journal of Statistical Planning and Inference 121, 113–125.

Keefer, P., Knack, S., 2002. Polarization, politics and property rights: Links between inequality and growth. Public Choice 111, 127–154.

Kelly, M., 2000. Inequality and crime. The Review of Economics and Statistics 82 (4), 530–539.

Knack, S., 2003. Groups, growth and trust: Cross-country evidence on the Olson and Putnam hypotheses. Public Choice 117, 341–355.

Knack, S., Keefer, P., 1997. Does social capital have an economic payoff? A cross-country investigation. Quarterly Journal of Economics 112 (4), 1251–1288.

Koenker, R., 2005. Quantile Regression. Cambridge University Press.

Koenker, R., Machado, J.A.F., 1999. Goodness of Fit and Related Inference Processes for Quantile Regression. Journal of the American Statistical Association 94 (448), 1296–1310.

Li, Q., Huang, C., Li, D., Fu, T., 2002. Semiparametric smooth coefficient models. Journal of Business and Economic Statistics 20 (3), 412–422.

Lyssiotou, P., Pashardes, P., Stengos, T., 2008. Demographic versus expenditure flexibility in Engel curves. Empirical Economics 34 (2), 257–271.

Mankiw, G., Romer, D., Weil, D., 1992. A contribution to the empirics of economic growth. Quarterly Journal of Economics 107 (2), 407–437.

Olson, M., 1982. The rise and decline of nations. Yale University Press, New Haven, Connecticut.

Ottaviano, G., Peri, G., 2006. The economic value of cultural diversity: evidence from US cities. Journal of Economic Geography 6 (1), 9–44.

Owen, A., Videras, J., Davis, L., 2009. Do all countries follow the same growth path ? Journal of Economic Growth 24, 265–286.

Paap, R., Franses, P., Dijk, D., 2005. Does Africa grow slower than Asia, Latin America and the Middle East? Evidence from a new database classification method. Journal of Development Economics 77, 553–570.

Papagapitos, A., Riley, R., 2009. Social trust and human capital formation. Economics Letters 102 (3), 158–160.

Persson, T., Tabellini, G., 1994. Is inequality harmful for growth? American Economic Review 84 (3), 600–621.

Platteau, J.-P., 1994. Behind the market stage where real societies exist–Part II: The role of moral norms. Journal of Development Studies 30 (4), 753–815.

Putnam, R., 1993. Making democracy work: Civic traditions in modern Italy. Princeton University Press, Princeton, New Jersey.

Putnam, R., 2000. Bowling alone: The collapse and revival of American community. Simon & Schuster, New York.

Ram, R., 2008. Parametric variability in cross country growth regressions: an application of quantile-regression methodology. Economics Letters 99, 387–389.

Routledge, B., Amsberg, J., 2003. Social capital and growth. Journal of Monetary Economics 50 (1), 167–193.

Rupasingha, A., Goetz, S., Freshwater, D., 2006. The production of social capital in US counties. The Journal of Socio-Economics 35 (1), 83–101.

Sabatini, F., 2009. Social capital as social networks: A new framework for measurement and an empirical analysis of its determinants and consequences. The Journal of Socio-Economics 38 (3), 429–442.

Saint-Paul, G., Verdier, T., 1993. Education, democracy and growth. Journal of Development Economics 42 (2), 399–407.

Shimizu, K., Crow, E., 1988. Lognormal distributions: theories and applications. Marcel Dekker, New York.

Simonoff, J.S., 1996. Smoothing Methods in Statistics. Springer, New York.

Sirimaneetham, V., Temple, J., 2009. Macroeconomic stability and the distribution of growth rates. The World Bank Economic Review 23 (3), 443–479.

Stengos, T., Zacharias, E., 2006. Intertemporal pricing and price discrimination: a semi-parametric hedonic analysis of the personal computer market. Journal of Applied Econometrics 21 (3), 371–386.

Temple, J., 2001. Generalizations that aren't? evidence on education and growth. European Economic Review 45 (4–6), 905–918.

Wand, M., Jones, M., 1995. Kernel Smoothing. Chapman and Hall, London.

Whiteley, P., 2000. Economic growth and social capital. Political Studies 48 (3), 443–466.

World Bank, 2010. http://web.worldbank.org/WBSITE/EXTERNAL/TOPICS/EXTSOCIALDEVELOPMENT/EXTTSOCIALCAPITAL/0,,contentMDK:20193059~menuPK:418220~pagePK:148956~piPK:216618~theSitePK:401015,00.html2010Accessed on October 28, 2010.

Zak, P.J., Knack, S., 2001. Trust and growth. The Economic Journal 111, 295–331.