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Growth, Income and Regulation: a Non-Linear Approach

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GROWTH, INCOME AND REGULATION: A NON-LINEAR APPROACH*

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Abstract. This paper analyzes the effect on GDP growth of income (GDP per capita) and economic regulation. A simple theoretical framework presents two opposing views. We analyze the empirical relation using a non-linear dynamic panel data model with fixed effects. The result shows that the effect of regulation on growth depends on income. For low-income countries, there is little effect of changing regulation. For highly regulated middle-income countries, deregulation can increase growth. For high-income countries, deregulation leads to higher growth. Holding regulation constant, there is catch-up growth with a maximum at an intermediate income level.

JEL: C23, D70, H11, O40.
Keywords: Catch-up growth, economic freedom, fixed effects, GMM, specification tests.

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I. Introduction

This paper analyzes empirically the effect of economic regulation on GDP growth. We show that the effect varies with income (GDP per capita). The relationship is complex with non-linearities and interaction terms. Although theory suggests non-linearities, they have not been analyzed jointly before.

We present a simple theory which captures two opposing views on the role of the government. The most common of these views predicts that the relationship between growth and regulation is concave with a unique optimum for a non-extreme level of regulation, while the other predicts that the relationship is monotone. To accommodate both views, we base the empirical analysis on a flexible non-linear model.

The theory of development suggests including of income as an explanatory variable because poor countries can grow faster than developed countries by adopting their technology. Technological catch-up may accelerate the convergence of poor countries to the level of developed countries. The convergence may be fast or slow depending upon the regulatory environment. The effect of income on growth is likely to be non-linear, and the level of income may affect the relationship between regulation and growth.

We exclude most variables which are commonly included in other studies of growth.[1] Since our purpose is to find the net effect of regulation and many of these variables are affected by regulation, they do not belong in our analysis. Other variables measure different aspects of economic regulation. We do not include these variables individually but instead use the Fraser Institute Index of Economic Freedom as our measure of the level of regulation. Variables like the size of a country, its location, resource base, culture and quality of administration are not affected by regulation, at least not in the short to medium term. They are important for growth, but difficult to measure. Since they are approximately constant over our observational time period, we control for these variables by country-specific fixed effects. Similarly, we control for exogenous shocks to the world economy by including time-specific fixed effects.

Only a few of the many cross-country panel studies of economic growth consider the effect of the level of regulation. Easton and Walker (1997) showed that more regulation decreases

[1] For example, Barro (1997, Table 1.1) explains growth by the logarithm of GDP per capita and eight additional variables to catch country-specific differences: (1) school enrolment rate, (2) life expectancy, (3) fertility rate, (4) government consumption ratio, (5) rule of law index, (6) terms of trade change, (7) democracy index, (8) inflation. For a recent survey of the empirical growth literature, see Durlauf, Johnson and Temple (forthcoming).

growth. Gwartney, Lawson and Holcombe (1999) examined the direction of causality. They showed that regulation causes growth and that growth does not cause regulation. Haan and Sturm (2000) performed a check of robustness in the sense of Leamer (1983). They found that while the effect of regulation is not robust, the effect of changes in regulation is robust.

Our econometric approach is distinct from earlier studies of regulation. We estimate a dynamic panel data model with fixed effects using the optimal system-GMM estimator developed by Blundell and Bond (1998). Since theories about regulation and growth are vague about the functional form of the relationship, we specify a general parameterization of the regression function. We simplify the general specification by testing against non-parametric alternatives. Hence the approach is non-parametric in flavor.

We find strong evidence that the level of regulation affects economic growth. However, the effect depends on the level of income. The level of regulation has a negative effect on growth for high-income countries. This contradicts the view that an interior optimum of regulation exists in these countries. For middle-income countries, too much regulation is harmful; however, from a certain point further deregulation does not affect growth. For low-income countries, regulation has not much influence on growth. Hence, a country needs a certain level of income to benefit from deregulation.

Looking at growth and income, holding regulation constant, we find that the relationship is quadratic. This implies that a low-income country will grow relatively slowly, but at an accelerating rate until its income reaches an intermediate level. The growth rate will then gradually revert back to its initial level as the country becomes increasingly rich. The level of the quadratic pattern depends on the level of regulation and maximum growth is attained for a mid-level of income and a mid-level of regulation.

Section II presents the theoretical framework. Section III describes the data, and section IV outlines the estimation approach. We discuss the results in section V and provide concluding remarks in section VI.

II. Theory on the impact of regulation

In this section, we present a theoretical framework that can accommodate the main views of the profession regarding the effect of regulation on growth. It allows for interaction between regulation and income (as a measure of the level of economic development) in determining growth.

A. Market faults and government faults

The effect of regulation on growth can be described in terms of efficiency losses due to market faults and government faults. Intuitively, market faults are mechanisms which prevent an unregulated economy without a public sector from achieving the social planner's optimal outcome. Market faults may be reduced by manipulating the incentives of the economic agents in order to turn positive growth externalities into private gains and negative externalities into private costs. Government faults are mechanisms through which economic policies and their implementation reduce welfare.[2] Much regulation is introduced for reasons unrelated to growth, such as defense, buying of votes, redistribution to the poor, and rent-seeking of client groups. Such regulation may be costly in terms of economic growth, and consequently government faults may be reduced by deregulation.

Even when economists agree on what governments *can* regulate in order to optimize social welfare, disagreement tends to arise about whether governments *will* regulate with such goals in mind. This depends on the incentives of governments. The opinions about the behavior of governments can broadly be summarized as the optimistic view and the pessimistic view.

The optimistic view exists in two versions: (i) governments are inherently good or (ii) governments are forced to be good by the political system.[3] Both versions treat governments as benevolent dictators; that is, as agents who maximize aggregate social welfare or the welfare of the median voter. Governments try to remedy market faults and to minimize government faults.

The pessimistic view of government claims that politics is a complex process which involves agents with opposing interests. This applies not only to governments and parties, but also to the bureaucracies which implement the policies. The outcome of the process is unlikely to minimize the total impact of market and government faults and, thus, unlikely to maximize growth. Behind the pessimistic view is a wide range of theories; however, a common characteristic of these theories is that governments (often) create government faults without removing market faults.

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[2] Many government faults arise because of time inconsistency. It has often been found that the political process create myopia in decision making, whereas many policy decisions have long-run implications.

[3] The positive theory of policy decisions (i) was shaped by Tinbergen (1964), who started a long tradition of using modeling to maximize economic outcomes. Version (ii) was developed by Wittman (1995), who presented a political rational-expectations theory of democratic governments.

B. Formalization

The optimistic and pessimistic views can be illustrated in a simple model with market and government faults. The level of economic regulations is represented by an index, x. It is scaled so that low values correspond to a high level of regulation and high values correspond to a low level.[4] We discuss the relationship between income and growth in subsection C. In this section, we assume that income is fixed. The effect of regulation on the growth rate, g, is then a function of market faults, f_{mf}, and government faults, f_{gf}, which themselves are functions of x. The relationship between g and x is illustrated in Figure 1 as the curve labeled Growth.[5]

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FIGURE 1

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The effect of changing the level of economic regulation can be decomposed into two partial effects. Assume that all functions are differentiable. Then:

(1) $$\frac{dg}{dx} = \frac{\partial g}{\partial f_{mf}} \frac{\partial f_{mf}}{\partial x} + \frac{\partial g}{\partial f_{gf}} \frac{\partial f_{gf}}{\partial x}.$$

The first term on the right-hand side is the effect which arises because of a reduction in market faults (holding government faults constant). In Figure 1 the MF-curve shows growth as a function of market faults assuming no costs of regulation. The growth rate without any economic regulation is g_L. According to the optimistic view, less regulation increases market faults and more market faults decrease growth. Hence, the curve has a negative slope:

(2) $$\frac{\partial g}{\partial f_{mf}} \frac{\partial f_{mf}}{\partial x} < 0.$$

In contrast, the pessimistic view is that regulation has little or no effect on market faults. According to the pessimistic view the slope is 0.

The second term on the right-hand side of (1) is the effect which arises because regulation causes government faults (holding market faults constant). In Figure 1 the GF-curve represents the effect on growth of a reduction in government faults. Less regulation is assumed to decrease government faults and, consequently, to increase growth. This implies:

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[4] The index is also known as "economic freedom", the absence of regulation.

[5] The figure assumes that the two terms of the function are additive, $g(f_{mf}(x), f_{gf}(x)) = f_{mf}(x) + f_{mf}(x)$. The analysis does not make this assumption.

(3) $$\frac{\partial g}{\partial f_{gf}}\frac{\partial f_{gf}}{\partial x} > 0 .$$

The Growth curve is the sum of the MF-curve and the GF-curve. The GF-curve summarizes the costs of regulation, while the gains are captured by the MF-curve. As their slopes have opposite signs, additional assumptions are needed to determine the curvature of the overall Growth curve.

The optimistic view of government predicts that for a given level of regulation, specific policies are designed to maximize growth. An optimal decrease in regulation (an increase in x) will remove the largest government fault at the expense of introducing the smallest market fault. Accordingly, the signs of the second-order derivatives are:

(4) $$\frac{\partial\left(\frac{\partial g}{\partial f_{mf}}\frac{\partial f_{mf}}{\partial x}\right)}{\partial x} < 0 \quad \text{and} \quad \frac{\partial\left(\frac{\partial g}{\partial f_{gf}}\frac{\partial f_{gf}}{\partial x}\right)}{\partial x} > 0 .$$

This implies that the Growth curve is concave, $\partial^2 g/\partial^2 x < 0$, and a unique optimum, g_{max}, of regulation exists. Assuming that the effect of the smallest market faults is less than the effect of the largest government faults, and vice versa, then the optimal level of regulation, x_{max}, is located between no and full regulation. The curves in Figure 1 illustrate this case.

The pessimist view of government predicts that growth always decreases with higher regulation. The MF curve is horizontal, and the shape of the Growth curve is therefore equal to the shape of the GF curve. The optimum is always no regulation.

C. Regulation and the two types of growth: steady state and catch-up

In neo-classical growth theory developed countries grow along (almost) the same steady state path, where growth is determined by international technological progress, g^*. The theory of economic development operates with other steady states determined by traditional technologies. These steady states have two characteristics: i) low productivity, and consequently low income, and ii) slow technical progress, and consequently slow growth. Historically, the less developed countries used to grow along one of these paths. However, today all less developed countries have a mixture of modern and traditional technologies.

Less developed countries may grow faster than g^* if they adopt the techniques of the developed countries and are able to shift resources between traditional and modern sectors.[6] This is known as catch-up growth.

Some countries may not be able to shift the resources without political cost, however. The restructering generates large changes in the income distribution which may cause social unrest. Faced with these conditions, the government may implement policies which help stabilize the political situation and reduce the impact of the structural changes. The cost of the structural change may explain why many less developed countries have tried to isolate themselves from the global market in order to better control the process of change.

Since the nature of steady-state and catch-up growth differ both economically and politically, countries at different levels of development are likely to face different market and government faults. Differences in market and government faults imply differences in the level of growth, holding regulation constant, as well as differences in the marginal effects of regulation. This means that the optimal level of regulation is likely to depend on the level of development.

The importance of the relationship between growth and the level of development leads us to include the income level, y, in our econometric analysis alongside the economic regulation index. While the size of the technological gap suggests that the relationship between growth and income is negative, holding regulation constant, other considerations suggest the possibility of a non-monotonic relationship. Moreover, differences in the nature of steady-state and catch-up growth mean that it is important to allow for interaction between regulation and income in the determination of growth. Since it is difficult a priori to sign the expected effects of income, regulation and their interaction, this is another reason for using a flexible functional form in our econometric analysis.

III. Data and the economic regulation index

The only non-standard variable is the index of regulation, x_{it}, which is briefly presented in the following subsection. The other variables used are defined as follows. The growth rate, g_{it}, is average real GDP per capita growth for the past five years. These data are from the World

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[6] In the DCs the typical difference between best-practice and worst-practice firms within a sector is 2–3, and there are only small differences (less than 0.5) between sectors. In LDCs the difference between best-practice and worst-practice firms within a sector may be 10–20 and the typical productivity differences between the modern and traditional sectors may be 3–5.

Bank's World Development Indicators 2003.[7] The variable y_{it} is the logarithm of income, and income is GDP per capita in PPP prices taken from the Penn World Tables. The dataset is an unbalanced panel with 590 observations, covering 123 countries and the seven years 1970, 1975, ..., 2000.[8]

A. The Fraser Institute Economic Freedom Index

The index of regulation is compiled by a network of 50 NGOs and is made up of about 125 variables representing various aspects of economic regulation. The index is constructed every five years. It starts in 1970 with 57 countries and ends in 2000 with 123 countries. The index is defined by a group of well-known researchers, and it is documented in several publications from the Fraser Institute, see for instance Gwartney, Lawson and Block (1996) and Gwartney, Lawson and Emerick (2003). Recently, the European Journal of Political Economy published a special issue devoted to the measurement and applications of the index in various fields, see Haan (2003).

The construction of the index is controversial.[9] Fortunately, it is a fairly robust measure. Firstly, it is highly correlated with the two other independently compiled indices of regulation, namely the Heritage Foundation Index and the Transition Index for the post-communist countries (see European Bank for Reconstruction and Development). Secondly, the index is a weighted sum of a set of subindices for different fields. Most of the subindices are themselves highly correlated, so the aggregate index is fairly robust to alternative weighting schemes.[10] Furthermore, the subindices are mainly constructed from variables which have long been used to proxy for government behavior in studies of growth. We use the index as defined.

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[7] The data for the Republic of China (Taiwan) have been added. A few gaps in the growth data have been filled using data from various sources.

[8] The observations for Russia (1975, 1980, 1985, 1990) and Nicaragua (1985) have values of the regulation index below 2 and have been dropped.

[9] Most of the researchers behind the index are well known for a libertarian leaning and most of the NGOs collecting the data proclaim a liberal or business orientation. A large scale effort, however, has been made to use a consistent and transparent method.

[10] The robustness of the conclusions to the composition of the index is analyzed by Carlsson and Lundström (2002) and Leertouwer (2002).

B. Description of the data

Figure 2 shows the average regulation index for seven groups of countries over the period 1975–2000. The countries of the West and the Asian Tigers have pursued relatively liberal policies. These countries have regulation levels between 6.5 and 8. On the Indian subcontinent and in Africa most countries have pursued policies generally known as "Third World Socialism". They have regulation levels ranging from 3.5 to 5. Broadly speaking, most of Latin America has pursued "Structuralist" policies which are fairly regulatory, although not as much as those of the Indian-African group. The Latin American countries had levels of regulation around 5 until liberalization started 1985. The transition from socialism is very visible in the curve for post-communist countries.

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FIGURE 2

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Figure 3 is a scatterplot of growth against the regulation level. The data points with extremely high growth rates represent big oil producing countries in the 1970s. The most systematic extremes are the two Asian Tigers, Hong Kong and Singapore, who grew fast during most of the period and had very little regulation. The plot also shows that regulation and growth tend to be similar for countries in the same geographically area. The only group of countries distributed throughout the range of the index is the Latin American group. Note also that high or low growth rates tend to be persistent, as does the regulation level.

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FIGURE 3

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IV. Estimation of the regulation-growth relationship

In this section, we present the model and outline our econometric approach. The theory developed in Section II does not pin down a specific functional form for the relationship between growth, income and regulation. To prevent misleading conclusions, it is therefore important to avoid strong assumptions about the functional form. We use a flexible parametric approach and test the specifications against general non-parametric alternatives.

A. Modeling and estimation

We model the growth rate for country i at time t, g_{it}, as a function of the past choice of regulation, x_{it-1}, the log of past income, y_{it-1}, unobserved fixed effects for countries, α_i, and years, τ_t, and unobserved "shocks", ε_{it}. We assume the regression function has the form:

(5) $$g_{it} = \phi(x_{it-1}, y_{it-1}; \gamma) + \alpha_i + \tau_t + \varepsilon_{it},$$

where $\phi(.,.;\gamma)$ is a class of continuous functions on R^2 indexed by a parameter vector, γ, the ε_{it}s are independent across countries and time, and $E(\varepsilon_{it}|x_{it-1}, y_{it-1}, \alpha_i, \tau_t) = 0$. We also impose the normalizations $E(\alpha_i) = 0$ and $\tau_{1980} = 0$. We assume that $\phi(x_{it-1}, y_{it-1}; \gamma)$ has the following general form:

(6) $$\begin{aligned}\phi(x_{it-1}, y_{it-1}; \gamma) = {} & \gamma_0 + \gamma_1 y_{it-1} + \gamma_2 x_{it-1} + \gamma_3 y_{it-1}^2 + \gamma_4 x_{it-1} y_{it-1} + \gamma_5 x_{it-1}^2 + \gamma_6 y_{it-1}^3 + \gamma_7 x_{it-1}^3 \\ & + \gamma_8 x_{it-1} y_{it-1}^2 + \gamma_9 x_{it-1}^2 y_{it-1} + \gamma_{10} e^{-x_{it-1}} \\ & + \gamma_{11} y_{it-1}^4 + \gamma_{12} x_{it-1}^4 + \gamma_{13} x_{it-1} y_{it-1}^3 + \gamma_{14} x_{it-1}^2 y_{it-1}^2 + \gamma_{15} x_{it-1}^3 y_{it-1}.\end{aligned}$$

Apart from the exponential term, this is simply a fourth-order Taylor expansion. In the empirical section we show that this class is sufficiently general to describe the data.

Let w_{it-1} denote the vector of explanatory variables in equation (6), including the constant term. Equation (5) can then be written:

(7) $$g_{it} = \gamma' w_{it-1} + \alpha_i + \tau_t + \varepsilon_{it}.$$

Estimation of (7) is complicated by the fact that the α_is are necessarily correlated with the y_{it}s and may also be correlated with the x_{it}s. In panel data sets where the number of time periods is large, this problem can be overcome by treating the α_is as parameters to be estimated. However, this is not an option here where the number of time periods is at most seven. To proceed we instead assume that $E(\varepsilon_{it}|x_{is-1}, y_{is-1}, \alpha_i, \tau_s) = 0$ for $s = 1,...,t$. This assumption, known as "predeterminedness" or "weak exogeneity" of the regressors, enables GMM estimation using functions of lagged x_{it}s and y_{it}s as instruments. This assumption is relatively weak. For example, it allows the level of economic regulation to be correlated with contemporaneous and past values of income as well as contemporaneous and past growth rates.

There is now a vast literature on the estimation of linear dynamic panel data models with fixed effects. Anderson and Hsiao (1981) were the first to consider first-differencing as a means of eliminating the country-specific effects:

(8) $$\Delta g_{it} = \gamma' \Delta w_{it-1} + \Delta \tau_t + \Delta \varepsilon_{it}.$$

First-differencing leads to an endogeneity problem since y_{it-1} (in w_{it-1}) is correlated with ε_{it-1} (in $\Delta\varepsilon_{it}$). Anderson and Hsiao suggested solving the endogeneity problem by instrumental variables estimation using lagged endogenous variables as instruments. Arellano and Bond (1991) extended the analysis to a GMM context using all linear moment conditions and lagged dependent variables as instruments. Their estimation method is now known as "difference" GMM. Arellano and Bover (1995) first proposed a particular stationarity assumption which implies that equation (7) can be used to form estimable moment conditions using differences of the lagged dependent variables as instruments. Estimation based on both the difference equations (8) and the level equations (7) is known as "system" GMM. Blundell and Bond (1998) further developed system GMM and showed that it is often superior to difference GMM.

We use the system-GMM estimator in this paper. As mentioned, instruments are needed because y_{it-1} and possibly x_{it-1} are correlated with $\Delta\varepsilon_{it}$. The instruments are $w_{it-s-1,k}$ in the differenced equation (8) and $\Delta w_{it-s-1,k}$ in the level equation (7), where $s = 1,...,t-2$ and $w_{it,k}$ is the kth element of w_{it}. The time dummies serve as instruments for themselves. There are more instruments than regressors and, thus, the system is overidentified. Therefore, we use two-step GMM estimation, where the weight matrix is estimated in the first step and the parameters in the second step using the estimated weight matrix.[11] The two-step GMM estimator is asymptotically efficient.

B. Specification testing

Our econometric strategy is to find a model that fits the data well and is relatively parsimonious. This is accomplished by specifying a very flexible class of models, given in (6), and testing special cases against more general alternatives. We use two tests for this purpose. One is a standard Wald test of the validity of the special case within the general class given by (6). The other is a test of the special case against a more general non-parametric alternative. This test, which we call the ACH test, is based on a test proposed by Aerts,

[11] The explanatory variables are orthogonalized (using Gauss' qqr procedure) before estimation. The weight matrix in the first step is $Z'HZ$, where Z is the matrix of instruments and H is a proxy for the variance matrix of the moment conditions constructed by taking var(ε_{it})=1 and var(α_i)=0. The standard errors of the two-step GMM estimator are estimated using the finite-sample corrections proposed by Windmeijer (2005).

Claeskens and Hart (1999). Both specification tests are based on one-step GMM estimates, because the one-step GMM estimates of the covariance matrix has better properties.

Aerts, Claeskens and Hart (1999) proposed test statistics for several scenarios, but none which are directly applicable in our GMM framework. We adapt their robust test for general estimating equations (GEEs) to the current setting. We briefly outline the idea of the ACH test in the remainder of this section; further details are provided in the Appendix.

The ACH test exploits the fact that any continuous function can be represented as an infinite series, $\phi(x,y)=\sum_{k=1}^{\infty}\theta_k a_k(x,y)$, where the $a_k(.,.)$s, $k=1,2,\ldots$, are basis functions which span the space of continuous functions and the θ_ks are coefficients. The basis functions can be polynomials of increasing power, trigonometric functions with increasing periodicity, or splines with increasing number of knots. Whereas the basis functions are a matter of choice, the coefficients are generally unknown. Often a good approximation to the true function can be constructed by truncating the infinite sum (the more terms, the better the approximation).

The ACH test is a test of a specific parametric model against a general non-parametric alternative. Let $\phi_0(.,.;\gamma)$ be the regression function for the specific parametric model; that is, equation (6) or a special case of equation (6). The general non-parametric alternative is constructed by extending the specific model with terms from a series approximation,

$$\phi_r(x,y;\gamma,\theta_r)=\phi_0(x,y;\gamma)+\sum_{k=1}^{r}\theta_{r,k}a_k(x,y), \tag{9}$$

where the subscript r refers to the model extended with r-terms. If the specific model is correct, then the true values of the $\theta_{r,k}$s are 0. On the other hand, if the specific model is false, some of the difference between the specific and the true model should be picked up by the $\theta_{r,k}$s. The power of the test depends on how well the series (9) approximates the true function. In this paper, the $a_k(.,.)$s consist of any terms in (6) not included in the specific model plus a number of higher-order functions of the regulation index (spline terms, see the Appendix). The latter are included because the regulation index does not have a natural scale, and it is therefore particularly important to test for non-linearities in this direction.

The ACH test is based on score statistics. The coefficients in (9) are estimated by GMM for $r=0,\ldots,R$, where in practice R is usually between 5 and 10. A score-statistic is computed for each r, based on the extended model (9) but evaluated under the null with the $\theta_{r,k}$s set to 0. The ACH test statistic is the maximum over these numbers. Its distribution is non-standard, but critical values are provided by Hart (1997, p178).

V. Empirical results

This section presents the estimated regression function followed by a discussion of the effect of regulation and income on growth.

A. The preferred model

Table A1 in the appendix shows the results of the specification tests for model (6) and selected special cases of model (6). Model (6) itself is not rejected against the non-parametric alternative. The special case which omits the fourth-order terms (y^4_{it-1}, x^4_{it-1}, $x_{it-1}y^3_{it-1}$, $x^2_{it-1}y^2_{it-1}$, $x^3_{it-1}y_{it-1}$) is not rejected either against the non-parametric alternatives using ACH tests or against model (6) using a Wald test. However, omitting all third-order terms or the exponential term is rejected. Investigating the effect of dropping individual third-order terms, we find that the third-order interaction terms ($x_{it-1}y^2_{it-1}$, $x^2_{it-1}y_{it-1}$) and cubic in the log of income (y^3_{it-1}) can be dropped. Therefore, our preferred model is:

(10) $$g_{it} = \gamma_0 + \gamma_1 y_{it-1} + \gamma_2 x_{it-1} + \gamma_3 y^2_{it-1} + \gamma_4 x_{it-1} y_{it-1} + \gamma_5 x^2_{it-1} + \gamma_7 x^3_{it-1} + \gamma_{10} e^{-x_{it-1}} + \alpha_i + \tau_t + \varepsilon_{it} .$$

Dropping the remaining third-order term (x^3_{it-1}) or the exponential term ($e^{-x_{it-1}}$) is rejected. Also, any more general model is accepted.

The parameter estimates for the preferred model are shown in the left-hand side of Table A2, along with diagnostic statistics.[12] The over-identifying restrictions are not rejected (*p*-value 0.137). The model also passes the Arellano-Bond autocorrelation check, as the test for first-order autocorrelation in the first-differenced residuals is significant (*p*-value 0.000) while the test for second-order autocorrelation is insignificant (*p*-value 0.982).

When interpreting the estimation results, it is important to keep in mind that the country-specific fixed effects are not estimated. This implies that the expected level of growth cannot be inferred. Differences in expected growth for a given country can be inferred, however. Since the model includes several non-linear terms, the γ-coefficients are not easily interpretable and we therefore focus on a graphical representation of the regression function.

[12] Since the variables are orthogonalized sequentially, the coefficients measure the contribution of each variable over and above the contribution of variables which appear earlier in the table.

A contour plot of the preferred model is shown in Figure 4. The country-specific effect is set to 0 and the time-specific effect to its mean over the period. The level curves show the combinations of the regulation index and log(income) which have the same expected growth. It is clear from Figure 4 that the relationship between growth, income and regulation is complicated.

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FIGURE 4

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The theory outlined in Section II is concerned with the effect of regulation for a given level of income and catch-up effects for a given level of regulation. These topics are discussed in the next two subsections.

B. Effect of economic regulation and the views on government

The effect of economic regulation can be seen by graphing regulation against growth for different levels of income. Figure 5 shows how the estimated regression function varies with regulation when income is held constant. Three levels of income are considered, namely the 10th, 50th and 90th percentiles (in the sample).[13] We will refer to these three income levels as low-income, middle-income and high-income countries. Examples of countries near the percentiles are the low-income countries Pakistan 1980, Nigeria 1990 and Benin 2000; the middle-income countries Costa Rica 1980, Chile 1990 and Iran 2000; and the high-income countries United States 1980, Australia 1990 and Finland 2000. The curves in Figure 5 are drawn for the regulation levels observed in the sample for each of the three income levels. Pointwise 0.95-confidence intervals are also shown.

The figure shows that the effect of regulation on growth is very different for different levels of income. For low-income countries, it appears that regulation has no effect on growth. For middle-income countries, there is a negative effect of regulation (positive effect of deregulation) for values of the regulation index less than 5. For higher values, there is no effect of regulation. For high-income countries, the relationship is monotonic: less regulation implies higher growth. Hence, the estimates suggest that a country needs a certain level of development for regulation to influence growth. The effect of regulation is large (and

[13] The corresponding values of income are 1022, 4915 and 18398, and the values of log(income) are 6.93, 8.50 and 9.82.

negative) for middle-income and high-income countries. For example, a highly regulated middle-income country gains about 4 percentage points of growth by reducing regulation to a medium or low level. For high-income countries, reducing regulation from a medium to a low level of regulation implies a similar change in expected growth.

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FIGURE 5

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The results do not support the optimistic view of government. The optimistic view is that, for each level of income, there is a unique interior value of regulation which maximizes growth. As can be seen from Figure 5, for high-income countries the optimum is no regulation. Moreover, although an interior maximum cannot be ruled out, there is no significant effect of regulation for low-income countries and, thus, possibly no unique optimum. For middle-income countries the results also suggest that there may be many optima since the relationship between regulation and growth is more or less constant for levels of regulation above 5.

A formal test of an optimal interior level of regulation can be carried out by comparing the preferred model with a model with only linear terms in the regulation index:

(11) $$g_{it} = \gamma_0 + \gamma_1 y_{it-1} + \gamma_2 x_{it-1} + \gamma_3 y_{it-1}^2 + \gamma_4 x_{it-1} y_{it-1} + \alpha_i + \tau_t + \varepsilon_{it} .$$

This model is listed in Tables A1 and A2 as model B7. Model B7 cannot be rejected against the preferred model. The Wald test of (11) against (10) is 2.84, with a *p*-value of 0.092. That is, we cannot rule out that the optimistic view is false and that growth is maximized at an extreme level of regulation for all income levels.

The pessimist view may also not hold. For low-income countries, it seems that regulation has no effect on growth. This contradicts the pessimist view that a reduction in regulation will lead to higher growth. A formal test can be carried out by testing whether the slope is positive in model B7. The marginal effect of regulation on growth is $\gamma_1 + \gamma_5 y_{it-1}$. The Wald statistic for the hypothesis that the marginal effect is zero for low-income countries ($y_{it-1} = 6.93$) is 0.0005 with a p-value of 0.983.[14] Thus we cannot rule out the possibility that the pessimistic view is false.

[14] As the variables are orthogonalized before estimation, the test is computed using re-transformed estimates.

C. Catch-up growth

Less developed countries may grow faster than developed countries if they are able to adopt existing technologies. In the following we discuss catch-up effects.

Figure 6 shows the effect of log(income) on growth for different levels of regulation. The levels of regulation are 3.8, 5.4 and 7.2, corresponding to the 10th, 50th and 90th percentiles in the sample. Examples of countries at these percentiles are Portugal 1980, Poland 1990 and Ukraine 2000 at the low level, Norway 1980, Portugal 1990 and Haiti 2000 at the middle level, and Singapore 1980, Germany 1990 and Sweden 2000 at the high level. The figure shows that at each level of regulation, maximum growth rate is attained when the country is an intermediate income level. Thus, growth depends on both the level of income and the level of regulation. In the development of a given country, the growth rate is highest when income is at an intermediate level and the level of regulation is also intermediate.

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FIGURE 6

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The quadratic relationship is interesting, since the technoligical potential for catch-up growth is larger the lower the level of development. A formal test of the quadratic relationship can be carried out by testing the null hypothesis that growth depends only linearly on income. That is, we test whether the following model is an adequate description of the data:

(12) $$g_{it} = \gamma_0 + \gamma_1 y_{it-1} + \gamma_2 x_{it-1} + \gamma_4 x_{it-1} y_{it-1} + \gamma_5 x_{it-1}^2 + \gamma_7 x_{it-1}^3 + \gamma_{10} e^{-x_{it-1}} + \alpha_i + \tau_t + \varepsilon_{it} .$$

This model is strongly rejected against the preferred model. The *p*-value of the Wald test of (12) against (10) is 0.000 (the test value is 15.01). Thus, the quadratic relationship between growth and income is statistically significant.

The result that the relationship between income and growth is quadratic is consistent with the hypothesis that institutions in low-income countries tend to be weak and the objectives of governments are diverted from maximizing growth. Both market faults and government faults are therefore large and growth is relatively slow. The institutions in middle-income countries are stronger and hence these countries are better able to take advantage of catch-up growth. Once a high income level is reached, growth slows down as technological progress becomes its main source.

VI. Concluding remarks

The main purpose of this study is to analyze the effects of income and economic regulation on growth. Our theoretical background discussion highlights the possibility of important non-linearities, and this motivates our flexible econometric approach in the empirical part of the paper. We estimate several non-linear dynamic panel data models with country-specific and time-specific fixed effects. We choose our preferred model after an extensive specification search using Wald and ACH tests as diagnostic tools.

We conclude that there is no simple, linear relationship between growth, income and regulation. A low level of regulation is optimal for rich countries, and highly regulated middle-income countries can benefit from deregulation. However, regulation does not matter much for poor countries, nor for middle-income countries with low levels of regulation. Thus, neither the optimistic nor the pessimistic view of government is supported by the data. Holding regulation constant, poor and rich countries grow slower than middle-income countries. Thus, a certain level of development seems necessary for a country to take advantage of catch-up growth.

Appendix

A. ACH test

Aerts, Claeskens and Hart (1999) proposed a number of omnibus specification tests based on the Akaike information criterion.[15] This appendix describes our adaptation of their robust test for general estimating equations (GEEs) to our GMM framework.

Let $U_r(\gamma,\theta_r)$ be the vector of moment conditions for the model with *r* extended terms, see equation (9). The GMM objective function is a quadratic form in the moment conditions:

$$D(\gamma,\theta_r) = U_r^{'}(\gamma,\theta_r) W U_r(\gamma,\theta_r),$$

where W is a given weight matrix (see footnote 11).

The original ACH test is derived under the assumption that the first-order condition of the estimator can be written as a sum of independent terms. This condition does not hold in finite samples for the GMM-estimator, but it holds asymptotically. This can be seen by considering the first-order condition $h_r(\gamma,\theta_r) = 0$, where

[15] See also Aerts, Claeskens and Hart (2000).

$$h_r(\gamma,\theta_r)=\frac{\partial D(\gamma,\theta_r)}{\partial(\gamma^{'}:\theta_r^{'})^{'}}=\frac{\partial U_r(\gamma,\theta_r)}{\partial(\gamma^{'}:\theta_r^{'})^{'}}(W+W')U_r(\gamma,\theta_r)\,.$$

The vector $U_r(\gamma,\theta_r)$ is a sum of the *n* observations:

$$U_r(\gamma,\theta_r)=\sum_{i=1}^{n}U_{r,i}(\gamma,\theta_r)\,.$$

The derivative can therefore be written:

$$h_r(\gamma,\theta_r)=\sum_{i=1}^{n}\frac{\partial U_r(\gamma,\theta_r)}{\partial(\gamma^{'}:\theta_r^{'})^{'}}(W+W')U_{r,i}(\gamma,\theta_r)\,.$$

As the sample size goes to infinity, the matrix in front of $U_{r,i}(\gamma,\theta_r)$ converges in probability to a constant matrix and, thus, $h_r(\gamma,\theta_r)$ is approximately a weighted sum of independent $U_{r,i}(\gamma,\theta_r)$ terms.

The null hypotheses of the ACH test is $H_0:\theta_r=0,\ r=1,..,R$ and the alternative is $H_1:\theta_r\neq 0,\ \text{for some}\, r$. The version of the ACH test used here is a score statistic. This implies that only parameter estimates under H_0 are used. For given r$\geq$1, the functions are evaluated in $(\tilde{\gamma},0_r)$, where $\tilde{\gamma}$ is the GMM estimator under H_0 and 0_r is an *r*-dimensional vector of zeros. Define

$$A_r(\gamma,\theta_r)=\frac{\partial h(\gamma,\theta_r)}{\partial(\gamma^{'}:\theta_r^{'})^{'}}$$

and

$$B_r(\gamma,\theta_r)=\sum_{i=1}^{n}\frac{\partial U_r(\gamma,\theta_r)}{\partial(\gamma^{'}:\theta_r^{'})^{'}}(W+W')U_{r,i}(\gamma,\theta_r)U_{r,i}^{'}(\gamma,\theta_r)(W+W')\frac{\partial U_r(\gamma,\theta_r)}{\partial(\gamma^{'}:\theta_r^{'})}\,.$$

Then the test statistics is:

$$\tilde{T}=\max_{1\leq r\leq R}\frac{[\xi_r]_r{}'[\tilde{A}_r^{-1}]_r\left([\tilde{A}_r^{-1}\tilde{B}_r\tilde{A}_r^{-1}]_r\right)^{-1}[\tilde{A}_r^{-1}]_r[\xi_r]_r}{r},$$

where the notation $[M]_r$ denotes the lower right $r\times r$-submatrix of the matrix M and $\xi_r=h(\tilde{\gamma},0_r)$, $\tilde{A}_r=A_r(\tilde{\gamma},0_r)$ and $\tilde{B}_r=B_r(\tilde{\gamma},0_r)$.

The distribution of the test statistics is non-standard. Asymptotic critical values can be found in Hart (1997, p178). We conducted a small simulation study which showed that the adapted test has the correct size and good power when using a fixed weight matrix (one-step GMM estimation), orthogonalized explanatory variables and asymptotic critical values. The ACH tests reported in this paper are implemented in this way. Note that because of the weighting by r in the construction of the test statistic, the order in which the extended variables appear may influence the outcome of the test.

B. Results of specification tests

The columns Table A1 show each of the models considered. The first column is the general specification given in equation (10). The left-hand side of the table shows models with and the right-hand side models without the exponential term. The main part of the table indicates the variables which are included in each model, while the last two rows indicate the outcome of the Wald and ACH tests, respectively. In addition to the variables listed, all models include a constant and year dummies.

Wald tests are carried out for each model against all of the models in the table which are more general than the model under consideration. The second last row indicates alternative models against which the null is rejected; a dash indicates that the null is not rejected for any alternative. For example, model A5 is tested against models A3, A2 and A1 and none of the tests are significant. Model B5 is tested against models B3, B2, B1, A5, A3, A2 and A1 and rejected at the 5% level against model B3.

A similar set of ACH tests are carried out, except that each more general model is further augmented by four to six cubic spline terms in the regulation index (fewer terms if the model already has many variables excluded from the model being tested). The knots are equally spaced between the minimum and the maximum values of the regulation index. As mentioned in the previous subsection, all variables are orthogonalized before estimation and one-step GMM is used. The additional variables in the more general model are included in the order they appear in the left-hand side of table A1, with the spline terms added at the end. The results of the ACH tests are reported in the last row of table A1 in the same way as the results of the Wald tests. For example, model A5 is tested against models A5, A3, A2 and A1 and rejected against model A5 (i.e. the spline terms are significant). Model B5 is tested against models B5, B3, B2, B1, A5, A3, A2 and A1 and rejected at the 5% level against models B5, A5, B3, A3, A2 and A1.

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TABLE A1

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Model A4, equation (10), is our preferred model, because all models more general than model A4 are not rejected and all models immediately below model A4 in the nesting hierarchy are rejected (i.e. models A5, A6 and B4). Model B7, equation (12), is also not rejected, but some of the models which are more general than B7 are rejected (i.e. models A5 and A6).

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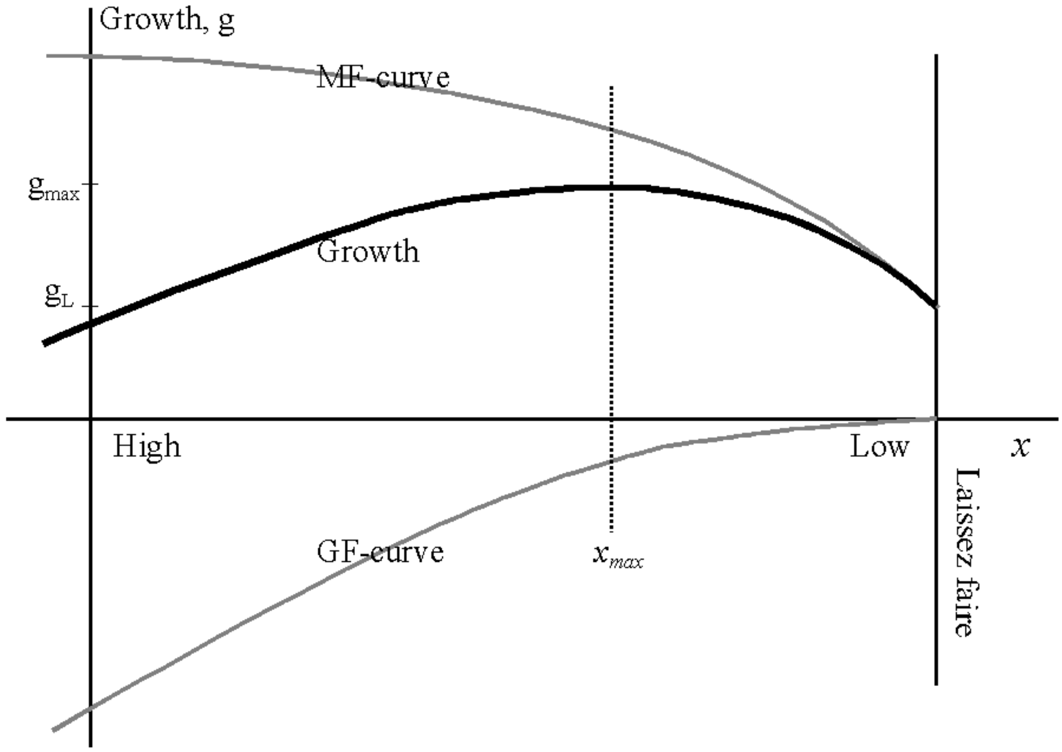

Figure 1. Effect of market and government faults on growth

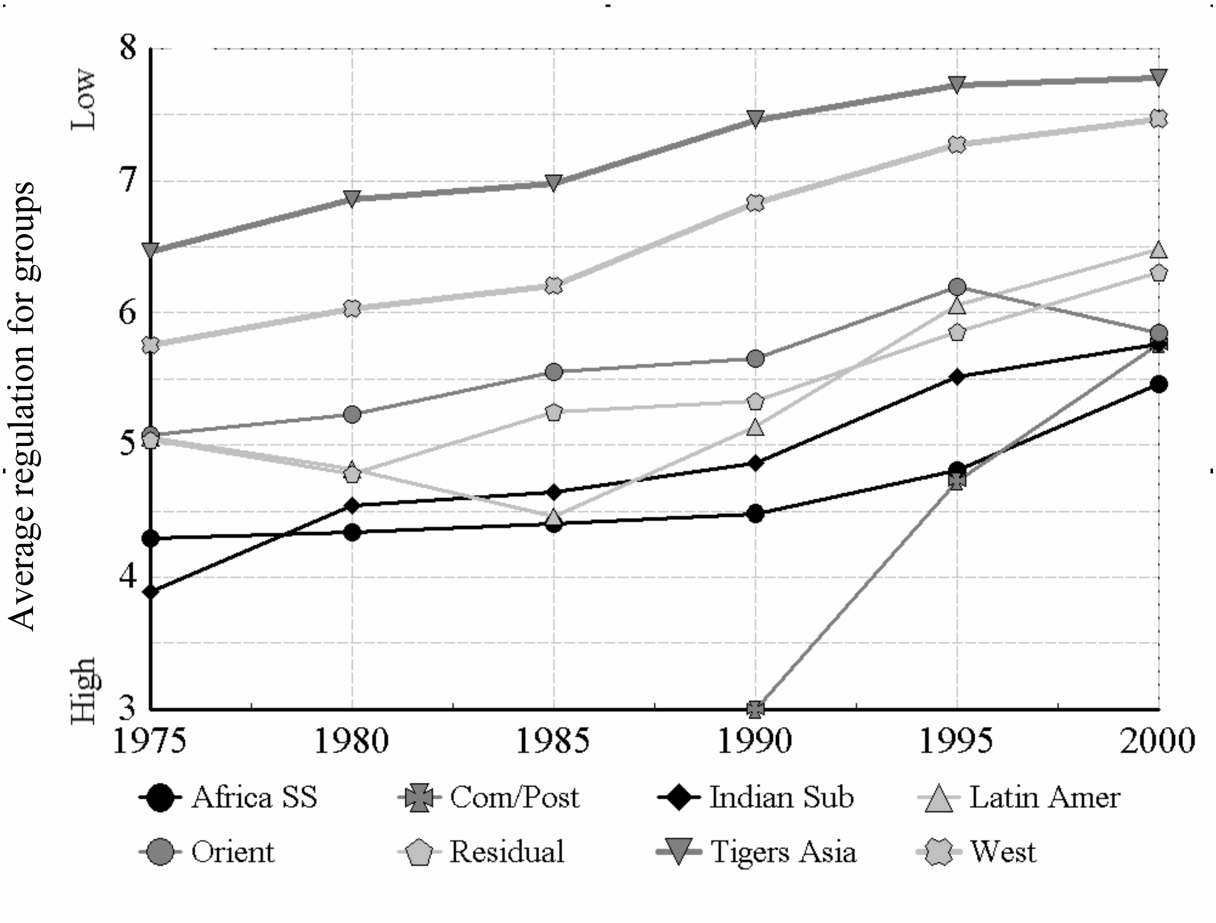

Figure 2. The average development of the regulation index for selected groups of countries

Note: The Asian Tigers are the five richest countries in the Orient, the Other Orient is East and South East Asia, excluding the Asian Tigers, SS means south of Sahara, Sub is subcontinent, Com/Post countries were communists before 1990. The countries of the groups are listed in Paldam (2003). The Residual group is not included in figure 2. A simple average is computed for each group over the countries with non-missing observations. In 1970, there are few observations on the index and consequeently the variance of the group mean is large. Therefore, the values for 1970 are not reported.

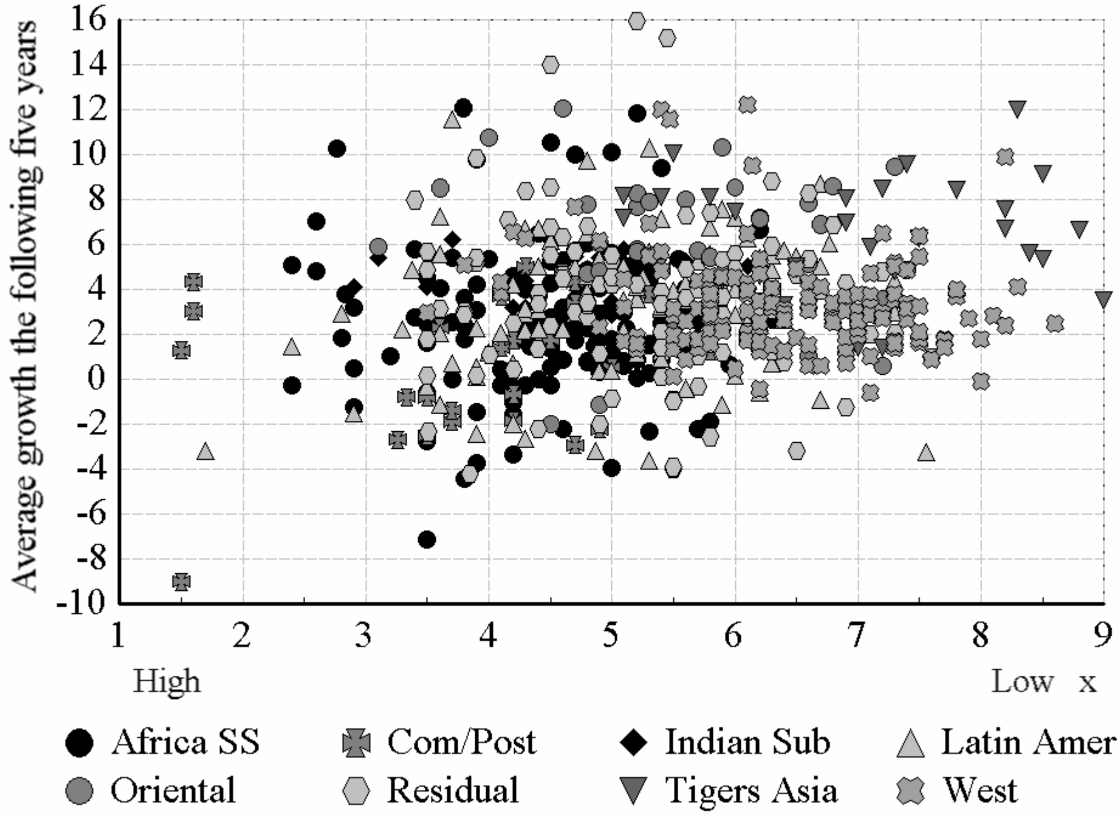

Figure 3. Scatterplot of regulation against growth

Note: See note to figure 2.

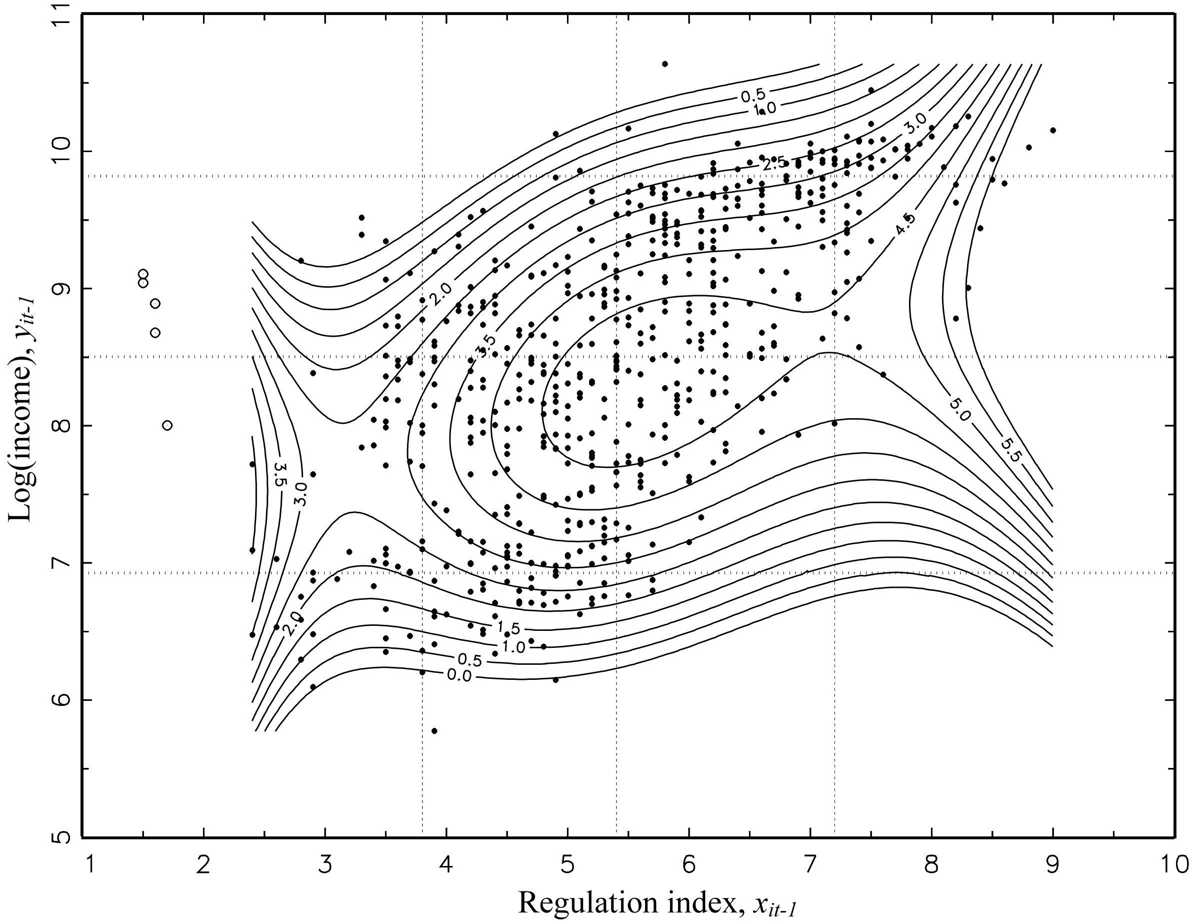

Figure 4. Contour plot of estimated regression function (preferred model)

Note: The country fixed effect is set equal to 0 and the total time effect is the weighted average with weights being inverse proportional to the cross-sectional sample size. Dots indicates observations used in the estimation and circles omitted observations.

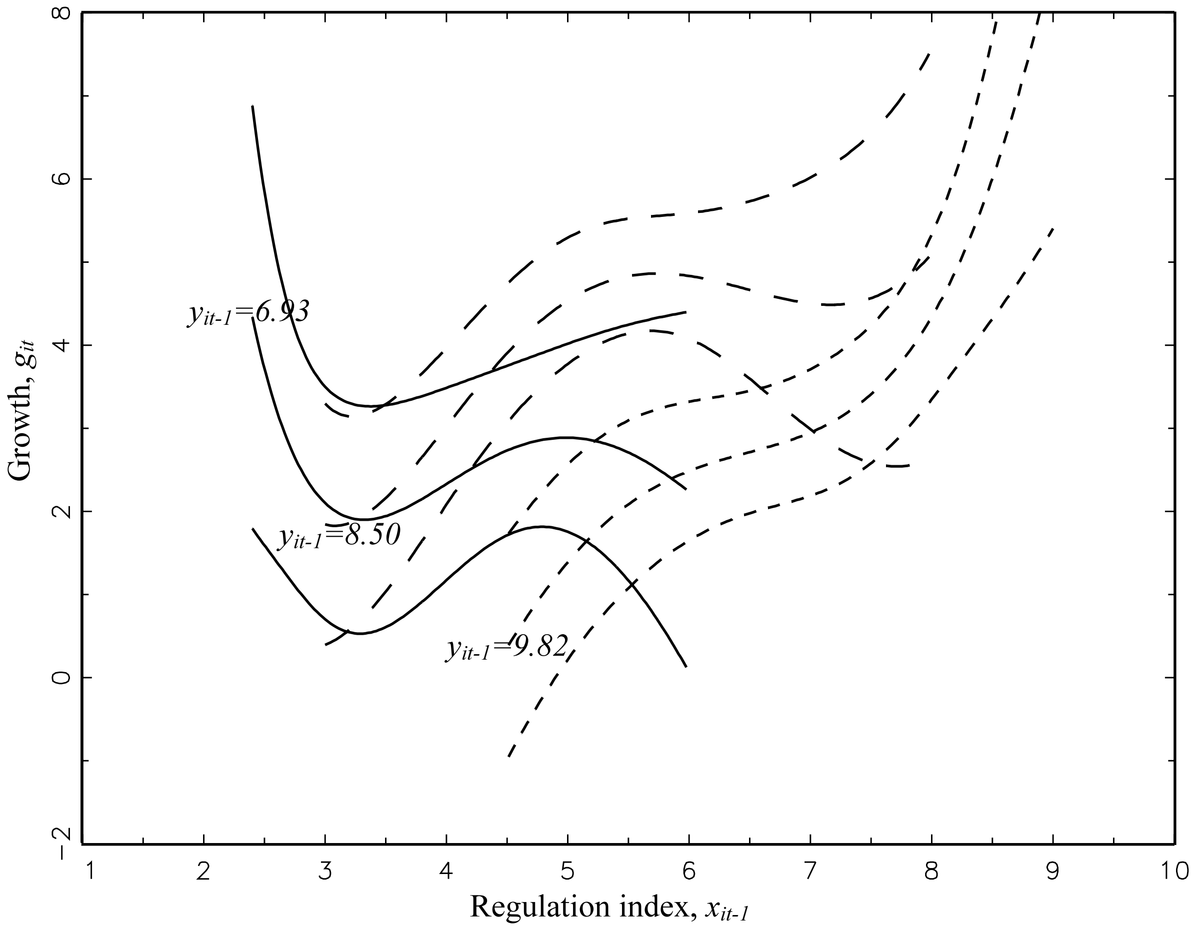

Figure 5. Regression function for given values of income

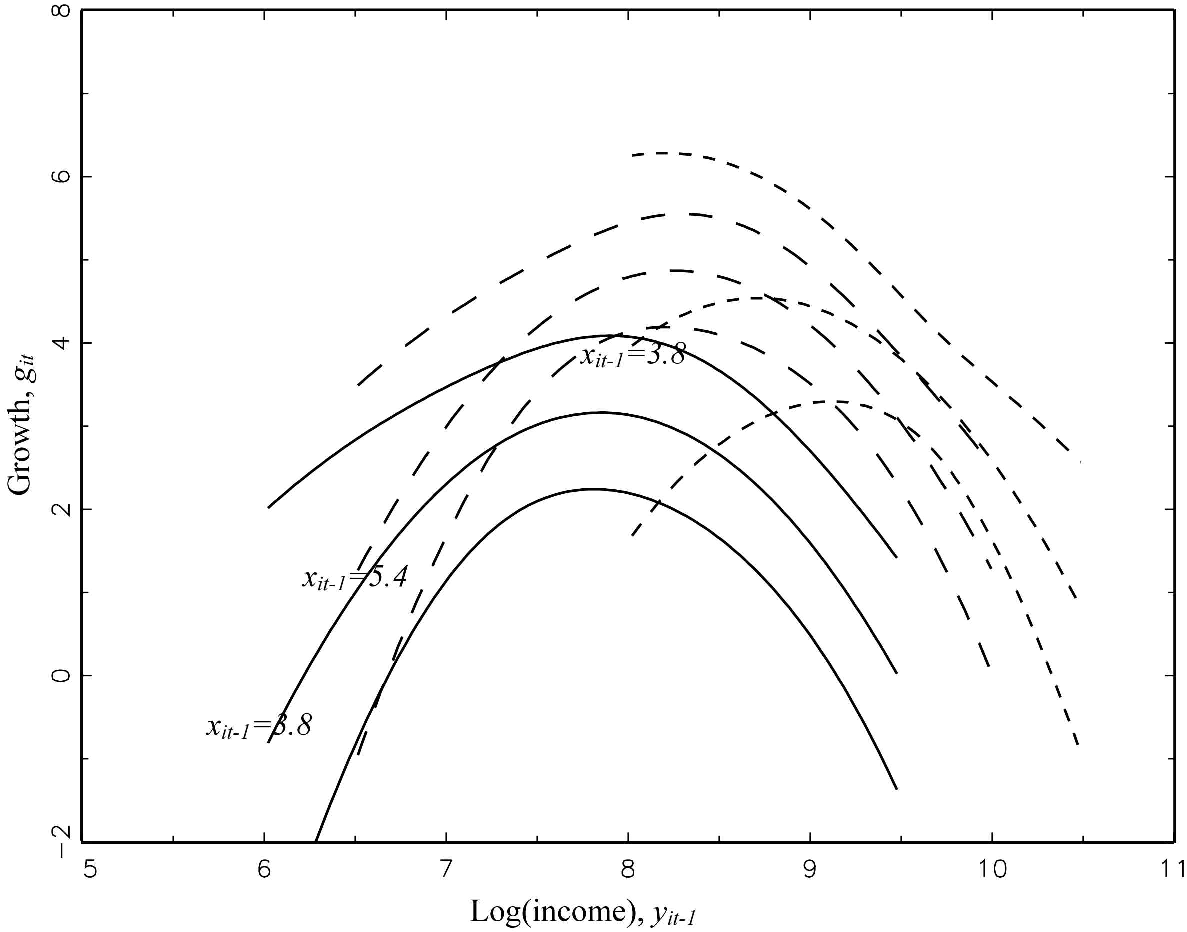

Figure 6. Regression function for given values of economic regulation

Table A1. Wald and ACH specification tests

Model	A1	A2	A3	A4	A5	A6	A7	A8	B1	B2	B3	B4	B5	B6	B7	B8
y_{it-1}	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
x_{it-1}	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
y_{it-1}^2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
$x_{it-1}y_{it-1}$	x	x	x	x	x	x	x		x	x	x	x	x	x	x	
x_{it-1}^2	x	x	x	x		x			x	x	x	x		x		
y_{it-1}^3	x	x	x		x				x	x	x		x			
x_{it-1}^3	x	x	x	x					x	x	x	x				
$x_{it-1}y_{it-1}^2$	x	x							x	x						
$x_{it-1}^2y_{it-1}$	x	x							x	x						
$e^{-x_{it-1}}$	x	x	x	x	x	x	x	x								
y_{it-1}^4	x								x							
x_{it-1}^4	x								x							
$x_{it-1}y_{it-1}^3$	x								x							
$x_{it-1}^2y_{it-1}^2$	x								x							
$x_{it-1}^3y_{it-1}$	x								x							
Wald rejections		-	-	-	-	-	-	A3 A4 A7	A1	A2	A3	A4	B3	A4 B4	-	B3 A4 B4 A6 A7 B7
ACH rejections	-	-	-	-	A5	A5 A6	-	All	A1 B1	A1 A2 B2	A1 A2 A3 B3	A4 B4	A1 A2 A3 B3 A5 B5	B3 B5 A4 B4 A6 B6	-	All but A8

Notes: Each column represent a particular model specification; the character "x" indicates variables included in the model, apart from a constant and year dummies which are always included. The last two rows indicate the outcome of testing each specific column model against all more general models (which nest the specific model). The entries show the alternative models against which the specific model is rejected at the 5% level; the character "-" indicates that the specific model is not rejected. For the ACH test the general models include higher-order spline terms for the regulation index (not indicated).

Table A2. GMM estimation results for growth models

	Preferred model		Model B7	
	Estimate	SE	Estimate	SE
constant	-83.63	4.20	-83.63	4.62
τ_{1975}	13.82	2.91	14.35	3.17
τ_{1985}	9.97	2.89	10.19	3.01
τ_{1990}	1.18	2.25	1.33	2.62
τ_{1995}	9.41	2.68	8.62	2.95
τ_{2000}	9.64	3.06	9.91	3.09
y_{it-1}	-4.39	5.17	-2.02	6.15
x_{it-1}	12.57	5.48	19.95	7.13
y_{it-1}^2	21.57	6.66	22.28	7.34
$x_{it-1}y_{it-1}$	8.01	3.57	12.30	4.72
x_{it-1}^2	-3.85	3.93		
x_{it-1}^3	3.91	3.80		
$e^{-x_{it-1}}$	10.33	3.56		
	Value	*p*-value	Value	*p*-value
GMM	105.8	0.137	98.18	0.044
NMC	104		86	
DF	91		76	
AR(1)	-4.63	0.000	-4.59	0.000
AR(2)	-0.02	0.982	-0.09	0.925

Legend: Std: standard error; GMM: GMM criterion value and *p*-value of Hansen's J test; NMC: number of moment conditions; DF: degrees of freedom; AR(s): Arellano-Bond test for AR(s) in first differences. *Notes*: Two-step "system" GMM estimates. Lags 1–2 used as instruments in the preferred model, while all lags used in the smaller models. The variables are orthogonalized before the analysis (using the qqr procedure in GAUSS 6.0) in the order they appear in the table. Number of countries: 122. Number of observations: 590.