

Stolzenburg, Ulrich

Working Paper

Growth determinants across time and space: A semiparametric panel data approach

Economics Working Paper, No. 2014-11

Provided in Cooperation with:

Christian-Albrechts-University of Kiel, Department of Economics

Suggested Citation: Stolzenburg, Ulrich (2014) : Growth determinants across time and space: A semiparametric panel data approach, Economics Working Paper, No. 2014-11, Kiel University, Department of Economics, Kiel

This Version is available at:

<https://hdl.handle.net/10419/102735>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

C | A | U

Christian-Albrechts-Universität zu Kiel

Department of Economics

Economics Working Paper
No 2014-11

growth determinants across time and space: a semiparametric panel data approach

by Ulrich Stolzenburg

issn 2193-2476



GROWTH DETERMINANTS ACROSS TIME AND SPACE

A SEMIPARAMETRIC PANEL DATA APPROACH¹

ULRICH STOLZENBURG

*Department of Economics Olshausenstr. 40, 24118 Kiel
University of Kiel, Germany E-Mail: stolzenburg@bwl.uni-kiel.de*

September 2014

Abstract: A panel data set covering 145 countries between 1960 and 2010 has been investigated closely by using models of parameter heterogeneity. The Functional Coefficient Model (FCM) introduced by Cai, Fan and Yao (2000) allows estimated parameters of growth determinants to vary as functions of one or two status variables. As a status variable, coefficients depend on the level of development, measured by initial per capita GDP. In a two-dimensional setting, time is used as an additional status variable. At first, the analysis is restricted to bivariate relationships between growth and only one of its determinants, dependent on one or both status variables in a local estimation. Afterwards, the well-known Solow (1956) model serves as a core setting of control variables, while functional dependence of additional explanatory variables is investigated. While some constraints of this modeling approach have to be kept in mind, functional specifications are a promising tool to investigate growth relationships, as well as their robustness and sensitivity. Finally, a simple derivation of FCM called local mean values provides a suitable way to visualize macroeconomic or demographic development patterns in a descriptive diagram.

Keywords: economic growth, cross-country growth regression, functional coefficient model, varying parameter, parameter heterogeneity, kernel regression, panel data, local mean value

¹ I thank Prof. Helmut Herwartz for initial help, valuable comments and suggestions.

Contents

1	Introduction	1
1.1	Related Literature: A Brief Overview	2
2	Dataset and Model Setup	3
2.1	Dataset and Status Variable	3
2.2	One-Dimensional Status Dependence	4
2.2.1	Model	4
2.2.2	Visualisation of Local Coefficients	6
2.2.3	Local Mean Value	7
2.2.4	Local Correlation	7
2.3	Local Estimation in Two-Dimensional Space	8
2.3.1	Model	8
2.3.2	Visualisation of Local Coefficients	9
3	Bivariate Growth Analysis	10
3.1	Selection of Explanatory Variables	10
3.2	An Aghion-Howitt Model Revisited	11
3.3	Macroeconomic and Demographic Measures	13
4	Functional and Constant Coefficients Combined	15
4.1	Prefiltering of Control Variables	15
4.2	Selected Results	16
5	Spin-Off: Contours of Development	19
6	Conclusion	21

1 Introduction

Improved data availability and computing power gave birth to large empirical studies searching for determinants of growth during the last 30 years. A popular method turned out to be cross-country growth regressions, trying to uncover relationships between per-capita growth rates and supposedly growth-relevant measures in a multiple regression model. Explanatory variables in these regressions covered macroeconomics, demographic and geographic characteristics, education measures, political and social indicators and even the prevalence of certain diseases. A numerous but still incomplete list of variables that have been applied in growth regressions is provided by *Durlauf, Johnson and Temple (2005)*.

Without mentioning, most of these empirical studies assume parameter homogeneity, that is, a certain explanatory variable is expected to have a homogeneous influence on economic growth across countries and years. *McCartney (2006)* denotes this procedure the ‘assumption of universalism’ - which exposes the view that each statistical observation will shed light on a universal underlying economic relationship, no matter when and where it has been observed.

Some authors deny this assumption of universal growth determinants. For example, *Sala-i-Martin and Artadi (2004)* rank countries according to their definition of competitiveness, which supposedly influences future growth prospects. According to this concept, there are three different stages of development in which different input factors are most relevant for a countries’ growth prospects.² Put differently, certain economic variables are of changing importance for growth, depending on the stage of development. *Aghion and Howitt (2006)* argue that countries with highly developed technology will accomplish further improvements of their productivity only by innovation, while less developed countries primarily need to adapt available technologies in order to enhance growth prospects. Therefore, economic policy and the design of institutions should depend on a countries stage of development. As a result, capital accumulation and the adaption of available technologies serve as a powerful growth engine as long as the country is somewhat distant to the technological frontier. The closer an economy converges to the technological frontier, the more important becomes, for example, attainment of higher education for further growth prospects. Again, changing success factors to foster economic growth are highlighted dependent on a countries’ development stage. With regard to growth regressions, this implies coefficients for mentioned variables to be dependent on the stage of development.

A suitable way to investigate functional dependencies of estimated coefficients is provided by *Cai, Fan und Yao’s (2000) Functional Coefficient Models (FCM)*, which was applied in a different

² The underlying idea is that economic development is following three subsequent stages: In the *factor-driven* stage, basic economic requirements are considered crucial for development: Quality of institutions, infrastructure, macroeconomic stability, personal security and basic human capital. In the second, *efficiency-driven* stage, a growing importance is attached to advanced human capital, efficiency of goods markets, labor markets and financial markets, ‘technological readiness’ and access to markets. During the *innovation-driven* stage of development, capability to innovate and business sophistication are considered most important. See *Snowdon (2006)* for more details.

context by *Herwartz* and *Xu* (2007). It is a multivariate version of the non-parametric *Nadaraya-Watson-Estimator*³ and allows for local estimation depending on one (or more) economic status variables. FCM is considered a semi-parametric approach, since a linear (parametric) model is estimated locally by a nonparametric method, which is Kernel regression (cf. *Härdle*, 1990). For instance, in the light of arguments of *Aghion* and *Howitt* (2006) the status variable indicates the stage of development of an economy. Using FCM, estimated functional parameters can be plotted against the underlying status variable in a suitable diagram. This way, we are able to investigate whether an economic relationship changes during the stages of economic development, but we may also confirm that it remains rather stable as is implicitly assumed in conventional growth regressions. The aim of this study is an investigation of functional dependence of coefficients in empirical growth models. Thereby, we weaken the restrictive assumption of universalism, i.e. we allow estimated parameters of growth determinants to vary across development stages. In a setting with two status variables, we also allow coefficients to change over time.

The remainder of this paper is structured as follows: Section 1.1 provides a brief overview on existing literature modeling economic growth with parameter heterogeneity. Section 2 describes briefly the composition of our panel dataset, followed by descriptions of statistical methods and diagrams used throughout the paper. The paper presents selected results with regard to a bivariate setting (section 3), a multivariate model with partial least squares prefiltering (Section 4), followed by some examples of two-dimensional local mean values, which provide a useful visualization of macroeconomic and demographic panel data (Section 5). Section 6 concludes.

1.1 Related Literature: A Brief Overview

Explicit modeling of varying parameters has been conducted by several studies. *Durlauf* and *Johnson* (1995) use average growth rates between 1960 and 1985 and divide their sample of 96 countries into four groups according to output level and literacy in order to generate four subsamples. Estimated coefficients in each regression differ considerably in sign, magnitude and p-value, so *Durlauf* and *Johnson* conclude that there are considerable differences between the groups which may be explained with a perspective of different steady states for each subsample. At the same time, countries of similar initial conditions may obey the same linear model.

Liu and *Stengos* (1999) use a semiparametric partially linear approach for the augmented *Solow* model from *Mankiw* et al. (1992), in which they allow the coefficients of initial GDP and of initial human capital investment to vary for different values of the respective explanatory variable. Data covers 86 countries from 1960 to 1990 in three 10-year-averages for all included variables. They find that there is a threshold effect, such that a growth-dampening effect of high initial GDP is only valid if initial GDP exceeds \$ 1800. Similarly, results suggest that secondary school enrollment (as a measure of human capital formation) fosters growth only for values beyond 15 %. Similarly to *Durlauf* and *Johnson* (1995), findings of *Liu* and *Stengos* (1999) suggest that

³ See *Nadaraya* (1964) and *Watson* (1964).

there might be different growth regimes and different equilibria.

Durlauf, Kourtellos and Minkin (2001) allow for parameter heterogeneity also in the augmented *Solow* model, while they use initial GDP per capita as a status variable. Explanatory variables are population growth, investment and initial human capital, such that they use a theory-based small setting for their cross-country growth regression model. Data covers 98 countries with average growth rates over the whole period between 1960 and 1985. They conclude that there appears to be a considerable degree of parameter heterogeneity in the data, without providing an explicit interpretation of locally estimated parameters. Instead, a general finding is that growth rates, the magnitude of local parameters as well as estimated residuals vary considerably more for the poorest countries. Accordingly, local measures for goodness-of-fit reach a much higher level for countries with a high initial GDP. *Kourtellos (2002)* confirms the finding of parameter heterogeneity using the same smooth coefficient approach. Instead of initial GDP, he uses initial literacy and initial life expectancy as status variables for dependent local parameters. Additional studies investigating parameter heterogeneity and finding considerable nonlinearities with regard to economic growth regressions are *Ketteni, Mamuneas and Stengos (2007)*, *Mamuneas, Savides and Stengos (2006)* as well as *Vaona and Schiavo (2007)*.

2 Dataset and Model Setup

2.1 Dataset and Status Variable

The data set is combined from two sources. From ‘Penn World Tables’ Version 7.1 (*Heston, Summers and Aten, 2012*) annual data on per capita growth rates, GDP levels, investment and government shares between 1960 and 2010 are obtained. The second source is World Banks ‘World Development Indicators’ (World Bank, 2012) providing other macroeconomic measures, demographic variables and data on educational attainment.⁴

Measurement quality of real per capita GDP is not convincing throughout the whole dataset, since we observe considerable fluctuations of real GDP values that can hardly be explained by regular growth dynamics. Annual growth rate “jumps” of more than 10 percentage points, up or down, are recorded in 1150 cases out of about 7500 valid observations. Annual growth rates of more than 10 per cent, up or down, can be observed in 839 observations. A few extreme values may reasonably be explained by growth spurts (for example in East Asia) or economic and political turmoil. Nonetheless, there appears to be a considerable amount of measurement uncertainty in the data. Since too much additional uncertainty may jeopardize our goal of

⁴ Data availability: Time series from PWT are rather complete, except for countries of former Yugoslavia and Soviet Union and some developing countries. As a result, no more than about 10-15% of values are missing for measures drawn from Penn World Tables between 1960 and 2010. Data availability for WDI measures is rather mixed: While demographic variables offer almost complete time series for most countries and years, time series of macroeconomic variables and some of the educational attainment measures are incomplete more often with missing values in 20-25% of the cases.

explaining economic growth rates, extreme fluctuations have been reduced to some extent. To this end, a standard HP-Filter (*Hodrick and Prescott, 1997*) was employed on annual observations of real GDP per capita. Resulting trend growth rates, computed from HP-filtered GDP values, are used in subsequent growth regressions.⁵ Throughout this paper, per capita growth rates and explanatory variables were transformed to 5-year averages in order to focus on medium-run growth. Former HP-Pre-filtering ensures that discussed fluctuations of annual GDP values at the beginning and at the end of 5-year episodes do not affect the dependent variable too much. Each country in the dataset consists of up to 10 growth observations between 1960 and 2010.

Logarithm of real GDP per capita (measured in constant PPP-adjusted prices) is used as status variable. It is expected to capture and to rank the development stage of each country in the dataset at any point in time. Thus, the status variable contains initial GDP of each of the ten growth episodes. However, due to our choice, we exclude a few heavily oil- and gas-producing small countries from estimation, because growth rates are fluctuating strongly and GDP levels may not reflect their true stage of development.⁶ We also exclude countries with a population of less than one million in order to exclude tax havens and independent island groups whose economies may work differently. From 185 countries available both in the WDI and PWT datasets we use 145 countries in the following analysis.⁷

2.2 One-Dimensional Status Dependence

2.2.1 Model

A model equation for the growth rate $g_{i,t}$ is specified as follows:

$$g_{i,t} = x'_{i,t} \cdot \beta + e_{i,t}, \quad i = 1, \dots, N, t = 1, \dots, T, \quad (1)$$

where N and T are the cross sectional and time dimension number of observations, respectively, $x_{i,t}$ is the vector of a constant and one explanatory variable for country i at time t , β is a vector containing 2 corresponding coefficients and $e_{i,t}$ is the stochastic error term satisfying $E[e_{i,t}] = 0$.

⁵ HP-filtered time series of real GDP per capita for each country were computed by using a (small) smoothing parameter of 10, in order to smooth away only strong short-term fluctuations. Then, first and last values of the smoothed time series were replaced by actual values, such that a countries' overall growth record remains to be built upon observed values only. Trend growth rates are computed by taking logarithmic differences.

⁶ Annual GDP levels of these countries are influenced strongly by concurrent international oil prices and oil production quotas. Therefore growth rates as the dependent variable is influenced strongly by it, which is not the focus of our study. Moreover, some of these countries have very high average income levels, not capturing their real development stage. This might render the chosen status variable unsuitable, since these countries were to be found among the highly developed countries.

⁷ Exclusion of countries has been made by using arbitrary thresholds of at least one million people (which excludes 34 countries) and an average share of fuel exports of at most 80% of all merchandise exports in combination with a logarithm of GDP per capita of more than 9.5 (about US-\$ 13.300) which excludes additional 6 countries). Arbitrary thresholds were not chosen in order to influence results in any way.

The model equation for a one-dimensional FCM is

$$g_{i,t} = x'_{i,t} \cdot \beta(u_{i,t}) + e_{i,t}. \quad (2)$$

A local vector $\hat{\beta}(u_{i,t})$ is determined through minimization of the weighted residual sum of squares

$$RSS = \sum_{i=1}^N \sum_{t=1}^T \left[g_{i,t} - \sum_{k=1}^K \beta_k \cdot x_{i,t,k} \right]^2 \cdot K_h(u_{i,t} - \bar{u})$$

Local estimation at focus \bar{u} is carried out by computing

$$\hat{\beta}(\bar{u}) = \left(\sum_{i=1}^N \sum_{t=1}^T x_{i,t} \cdot x'_{i,t} \cdot K_h(u_{i,t} - \bar{u}) \right)^{-1} \cdot \sum_{i=1}^N \sum_{t=1}^T x_{i,t} \cdot g_{i,t} \cdot K_h(u_{i,t} - \bar{u}). \quad (3)$$

In this study, we rely exclusively on the Gaussian pdf as a Kernel function, denoted as $K_h(u)$:

$$K_h(u) = \frac{1}{h \cdot \sqrt{2\pi}} \cdot e^{-\frac{1}{2} \left(\frac{u}{h}\right)^2} \quad (4)$$

Note that (3) is reduced to the pooled least squares estimator, if multiplication of each term with Kernel function K_h is left out of the equation, that is, if we assign uniform weights to all available observations. In that case, estimates for β are no more dependent on focus \bar{u} . In other words, equation 3 is a ‘‘Pooled Least Squares’’ regression, augmented by a certain weighting scheme. The weights for each observation are dependent on the current focus \bar{u} of local estimation, such that observations with a status variable very close to \bar{u} are given a relatively high weight. Moving away from the estimation weight peak, weights are reduced according to the *pdf* of a Normal distribution. The local environment around \bar{u} will be given relevant weights capable to influence the local estimates, distant observations will be given weights close to zero.

Bandwidth Selection

Selection of a proper bandwidth parameter for the Kernel is crucial to allow for a useful interpretation of results. Loosely speaking, the higher bandwidth parameter h , the more smoothing will be done. A relatively high value of h ensures that more weight will be applied to more distant observations relative to the focus of local estimation. Estimated functional coefficients will be smoother if a larger value for the bandwidth parameter is chosen. On the other hand, a low value for h ensures that only observations in a very close environment to the focus will be given relevant weights in the estimation. In that case, functional coefficients are more volatile over the status variables support.

Local estimation can only provide reasonable results in an environment with a sufficient number of observations. Otherwise a functional coefficient estimate may be dominated by very few observations and will be characterized by strong fluctuations and weird estimates in that range.

To maintain confident with the results it is desirable to apply a slightly higher value for bandwidth parameter h when the density of observations is comparably thin at a certain local environment around \bar{u} . Therefore, local bandwidth parameters are selected dependent on the density of observations. Loosely inhabited environments of the status support will be smoothed stronger.⁸

2.2.2 Visualisation of Local Coefficients

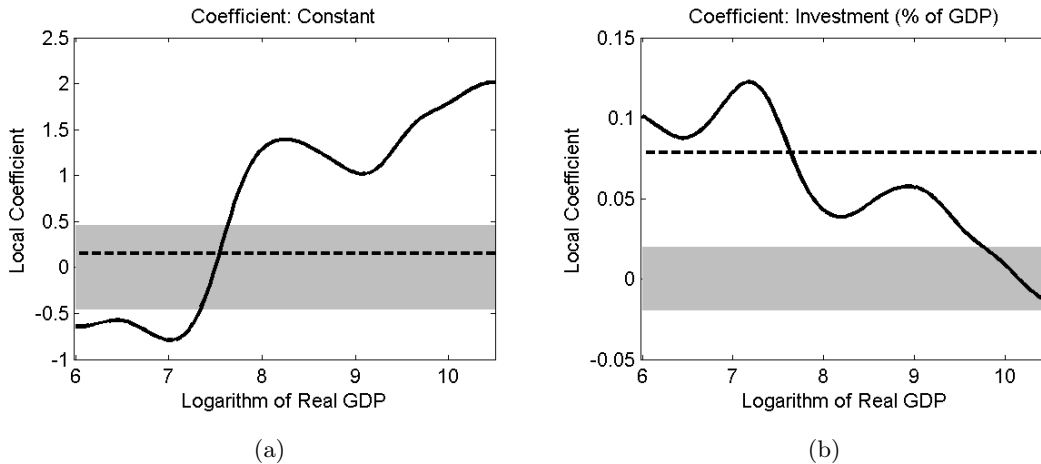


Figure 1: Functional coefficient estimates for 5-year growth rates between 1960 and 2010 as a dependent variable, using a constant and investment (% of GDP) as explanatory variables, $N=1267$, 1960-2010. (a) Functional coefficient of the constant, (b) Functional slope coefficient of investment in a one-dimensional FCM. The grey shaded area around 0 depicts the interval of coefficient values that are not considered significant at 5% level in pooled OLS estimation. The dashed line marks the pooled OLS point estimate.

Figures 1(a) and 1(b) depict the estimated functional coefficient values across the support of the status variable. The grey area around 0 can be considered the “area of insignificance”, i.e. coefficient values not significant at 5% confidence level in a pooled ordinary least squares (OLS) regression, while the dashed line depicts the pooled OLS point estimate of both parameters, respectively. The left figure 1(a) shows the intercept of the regression line in a scatter plot of

⁸ See *Jennen-Steinmetz and Gasser (1988)* for density-dependent local bandwidth selection. A two-stage approach for the choice of appropriate local smoothing parameters along the support of the status variable has been followed here. In the first stage, a fixed value of $h = 0.35$ served to compute a preliminary weighting scheme $K_h(u_{i,t} - \bar{u})$. The “effective number of observations“ for each point \bar{u} of the status support is computed as follows:

$$N_{eff}(\bar{u}) = \frac{\sum_{i=1}^N \sum_{t=1}^T K_h(u_{i,t} - \bar{u})}{\max(K_h(u_{i,t} - \bar{u}))}$$

Thus, all the weights given to observations across countries and years are summed up, divided by the maximum weight of the current local weighting scheme. In a second stage, local bandwidth parameters in dependence of N_{eff} are generated via:

$$h(\bar{u}) = \frac{1}{N_{eff}(\bar{u})^{\frac{1}{4}}}$$

A low number of effective observations at some point \bar{u} will result in a larger bandwidth parameter $h(\bar{u})$. Therefore, desired additional smoothing in loosely populated environments of the status support is done. Note that the bandwidth parameter of the functional coefficient model needs to be multiplied by the standard deviation of its status variable, if it is not normalized to a standard deviation of 1.

growth vs. investment with OLS estimation. Since the influence of explanatory variables on growth is of primary interest, following sections will focus on slope parameters only, leaving functional estimates of the constant in the dark.

2.2.3 Local Mean Value

By using the weighting scheme from functional estimation, we are able to compute weighted, local mean values of explanatory variables. In fact, this procedure is identical to using the variable $x_{i,t}$ as dependent variable and to regress it on a constant using FCM along the support of the status variable $u_{i,t}$ as before. They are computed for different values of \bar{u} as follows:

$$\bar{x}(\bar{u}) = \frac{\sum_{i=1}^N \sum_{t=1}^T x_{i,t} \cdot K_{u,h}(u_{i,t} - \bar{u})}{\sum_{i=1}^N \sum_{t=1}^T K_{u,h}(u_{i,t} - \bar{u})} \quad (5)$$

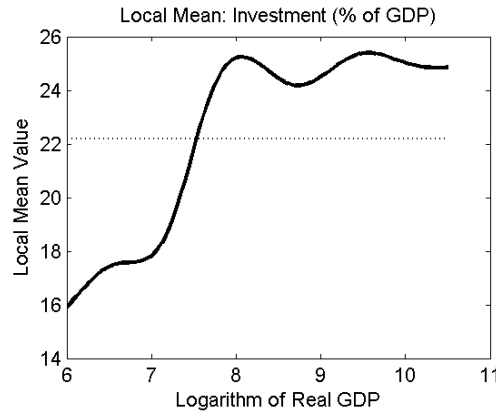


Figure 2: Local mean value of investment (% of GDP) over the support of the status variable, $N=1267$, 1960-2010. Dotted line depicts the non-weighted, overall mean.

Figure 2 shows locally weighted mean values of investment as a percentage of GDP. Average investment shares are lower for the poorest countries (16-18 %) compared to middle-income and rich countries (about 25 %). The global mean value for all 1267 observations of investment is slightly more than 22 %, which is depicted as dotted line.

2.2.4 Local Correlation

To compute a local correlation coefficient between growth (y) and some explanatory variable (x), we have to define the local variance as follows, in this case for x :

$$\sigma_x^2(\bar{u}) = \frac{\sum_{i=1}^N \sum_{t=1}^T (x_{i,t} - \bar{x}(\bar{u}))^2 \cdot K_{u,h}(u_{i,t} - \bar{u})}{\sum_{i=1}^N \sum_{t=1}^T K_{u,h}(u_{i,t} - \bar{u})}, \quad (6)$$

as well as the covariance between x and y :

$$\sigma_{x,y}(\bar{u}) = \frac{\sum_{i=1}^N \sum_{t=1}^T (x_{i,t} - \bar{x}(\bar{u})) \cdot (y_{i,t} - \bar{y}(\bar{u})) \cdot K_{u,h}(u_{i,t} - \bar{u})}{\sum_{i=1}^N \sum_{t=1}^T K_{u,h}(u_{i,t} - \bar{u})} \quad (7)$$

Thus, we are able to define a local version of *Spearman's* correlation coefficient, which is the local covariance between x and y divided by local standard deviation of x and y at point \bar{u} respectively:

$$\rho(\bar{u}) = \frac{\sigma_{x,y}(\bar{u})}{\sigma_x(\bar{u}) \cdot \sigma_y(\bar{u})} \quad (8)$$

Figure 3 shows estimated values for a local correlation coefficient between growth and investment along the support of the status variable. It is largely related to Figure 1(b), but gives an idea about the extent, to which investment is able to explain parts of the growth variation between countries and years. The dotted line depicts a correlation of zero. In this case the correlation between growth and investment is about 0.3 for poor countries and is decreasing with development stage. Among the richest economies, the correlation is approximately 0.

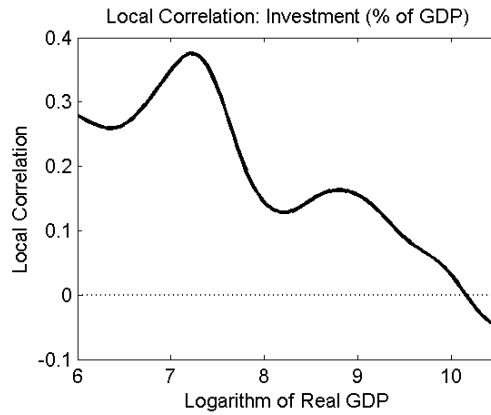


Figure 3: Local correlation coefficient of growth vs. investment (% of GDP) over the support of the status variable, $N=1267$, 1960-2010. Dotted line depicts a correlation of 0.

2.3 Local Estimation in Two-Dimensional Space

2.3.1 Model

Instead of only using the stage of development as a status variable, time might also be included as a second dimension of status dependence. This way it is possible to investigate the temporal development of functional relationships, such that structural breaks in the importance of a certain variable may be detected.

The model equation for a two-dimensional FCM is

$$g_{i,t} = x'_{i,t} \cdot \beta(u_{i,t}, w_{i,t}) + e_{i,t}. \quad (9)$$

Local estimation at focusses \bar{u} and \bar{w} is carried out by computing

$$\hat{\beta}(\bar{u}_i, \bar{u}_t) = \left(\sum_{i=1}^N \sum_{t=1}^T x_{i,t} \cdot x'_{i,t} \cdot K_{ih}(u_{i,t} - \bar{u}) \cdot K_{th}(u_{i,t} - \bar{w}) \right)^{-1} \cdot \sum_{i=1}^N \sum_{t=1}^T x_{i,t} \cdot g_{i,t} \cdot K_{ih}(u_{i,t} - \bar{u}) \cdot K_{th}(u_{i,t} - \bar{w}). \quad (10)$$

Note that the mere difference to (3) is a second weighting term K_{th} which sets an additional local estimation focus \bar{w} in the time dimension. Bandwidth parameters for both dimensions are selected equally to the one-dimensional case: In loosely populated areas of the status variables (in terms of available observations) a higher bandwidth parameter is selected to ensure additional smoothing.

2.3.2 Visualisation of Local Coefficients

Figure 4(a) depicts the functional coefficient of the two-dimensional model of growth vs. investment in a surface plot. Values for the slope parameter of investment are highlighted according to the color scale on the right. Figure 4(b) shows the corresponding contour plot. Both figures give rise to the impression that the relationship of growth and investment is strong and rather stable for poorer countries, while this relation is of decreasing importance or strength in richer economies. The relation even turns negative in recent years.

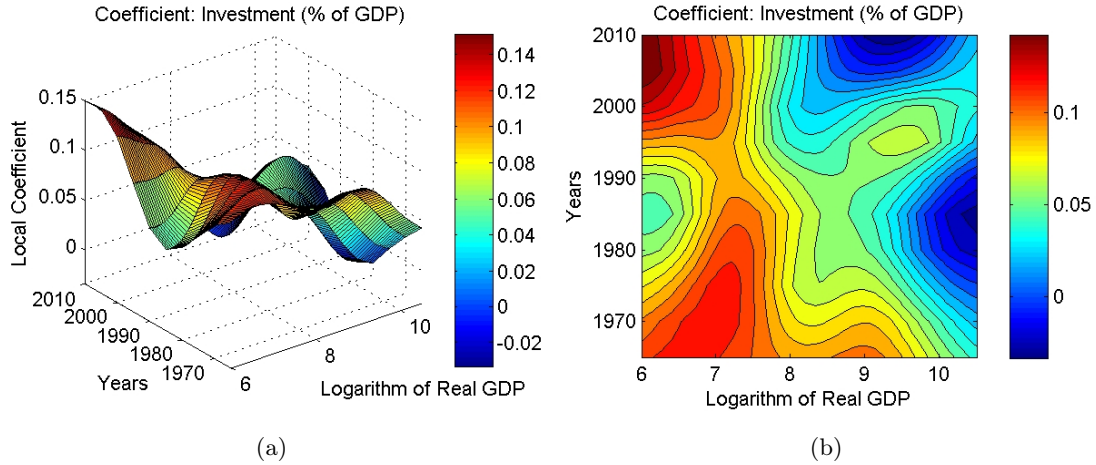


Figure 4: Functional coefficient estimates for 5-year growth average, using a constant and investment (% of GDP) as explanatory variables, $N=1267$, 1960-2010. (a) functional coefficient of a two-dimensional FCM as a surface plot, (b) the same functional coefficient in a two-dimensional FCM as a contour plot.

3 Bivariate Growth Analysis

3.1 Selection of Explanatory Variables

To reduce complexity, theoretical models of economic growth tend to emphasize one or very few aspects, but neglect other factors, that may also play an important role for real growth processes.⁹ Economic theory may contribute to the understanding of growth processes, but it does not provide a feasible and ready-to-use empirical model of all important causal relationships. *Henderson et al.* (2010) refer to this aspect as “variable uncertainty”.

A large number of possible explanatory variables have been investigated in cross-country growth regressions. *Durlauf et al.* (2005) provide a still incomplete list of 140 such variables. However, coefficients with expected sign and significance level in a certain setting of explanatory variables cannot be regarded as sufficient evidence for a stable or even causal relationship between the measure of interest and economic growth. For most variables it is possible to find specifications with coefficients below critical values or even reversed sign. *Levine and Renelt* (1992) performed a robustness analysis using more than 50 explanatory variables. The results were disappointing, because almost all relationships are very sensitive to alterations in the composition of explanatory variables, and in many settings even the sign of the coefficient was changing. *Sala-i-Martin* (2007), on the other hand, used a similar robustness analysis and found some variables with rather stable results.

Anyway, intuition suggests that “true” growth determinants are not at all related in a simple linear model. Their growth contribution is rather interdependent, some relationships may be hierarchical and highly complex. Moreover, each simple linear setting of explanatory variables gives rise to scepticism on the robustness of empirical findings with regard to the chosen combination of explanatory and control variables. This is even more true for functional estimates, because in this case there is not only a single point estimate of the corresponding coefficient, but a functional course across the support of the status variable instead. Apparently, a functional pattern for each coefficient is even more sensitive to alterations than a mere point estimate. In a two-dimensional functional coefficient approach, allowing for additional functional variation in the time dimension, we have even more reason to be doubtful about the robustness. Former approaches of parameter heterogeneity like *Liu and Stengos* (1999) and *Durlauf et al.* (2001) circumvented this difficulty and used a theory-based list of explanatory variables from *Mankiw et al.* (1993). The augmented *Solow* model captures investment, population growth and initial

⁹ The well-known *Solow* (1959) model highlights the role of factor accumulation, namely capital and labor endowment of an economy. Explicit modeling of innovation is not captured by this model, which is why modern growth models fill this gap by providing microfoundations for knowledge creation processes, resulting in a long-run growth rate dependent on human capital accumulation (*Lucas* (1988) as well as *Mankiw, Romer* and *Weil* (1992)), the level of research and development of new product variants (*Romer* (1986, 1990), *Grossman* and *Helpman*, 1991). Models of creative destruction, where newly developed products displace the old ones in an environment of temporal monopoly gains (*Aghion* and *Howitt*, 2006), provide another idea of the knowledge creation process and economic progress.

educational attainment. Nevertheless, there seems to be pretty low confidence in the estimated functional coefficients, when *Durlauf et al.* (2001) interpret their results considerably careful, claiming that “there appears to be a lot of heterogeneity in the data”.

Since no theoretical model provides an exhaustive list of explanatory variables; since there is doubt whether highly complex relationships can be approximated properly by a linear regression model; since functional estimates are even more sensitive to alterations in the list of explanatory variables than OLS results, the growth analysis in this section is simplified. Relationships of economic growth with a single variable at a time will be considered, dependent on chosen status variables. Apparently, a desirable quality of empirical growth analysis is a competitive test of certain measures in a multiple regression analysis.¹⁰ As *Durlauf et al.* (2005) put it, a less ambitious goal is pursued here, namely to investigate whether or not particular relationships have any support in the data at all. Patterns and systematic tendencies of the co-occurrence and correlation of certain parameters with good or bad growth records will be investigated with regard to the accompanying development stage of a country.

3.2 An Aghion-Howitt Model Revisited

A closer investigation of the relation between a countries' growth and savings rate is provided here. *Aghion und Howitt* (2006) argue that middle-income countries need technological spill-overs from higher developed countries to catch up with the technological frontier. Technology transfer occurs when technologically leading firms from developed economies conduct direct investments. To attract those foreign direct investments, the domestic climate for investments is crucial, i.e. infrastructure, macroeconomic stability, social peace. The governments willingness to create this fruitful investment climate is necessary and for this purpose economy-scale savings are needed, as *Aghion und Howitt* argue. In highly developed countries, on the other hand, the ability to create savings is not that crucial, because further growth is accomplished rather by innovations, not by adaption of existing technologies. Therefore growth is not that dependent on savings any more. With regard to poor countries, which are very far from the technological frontier, total economic costs for the creation of such a favorable investment climate are relatively high, so savings are not that important for this group of countries as well. To investigate the relationship between growth and savings, *Aghion und Howitt* divide their sample into three subsamples of poor, medium-income and rich countries and regress average growth rate between 1960 and 2000 on a constant and the savings rate. In the group of poor and rich countries, they found the savings rate not to be significantly related to growth, while the medium income group resulted in a significantly positive influence of economic savings on growth. Therefore, above mentioned hypotheses could be confirmed empirically.¹¹

Compared to arbitrary sample division, functional estimation provides a more elegant way to estimate this relation. Again, the logarithm of real GDP per capita is used as a status variable.

¹⁰This will be provided in section 4 to some extent.

¹¹See *Aghion und Howitt* (2006).

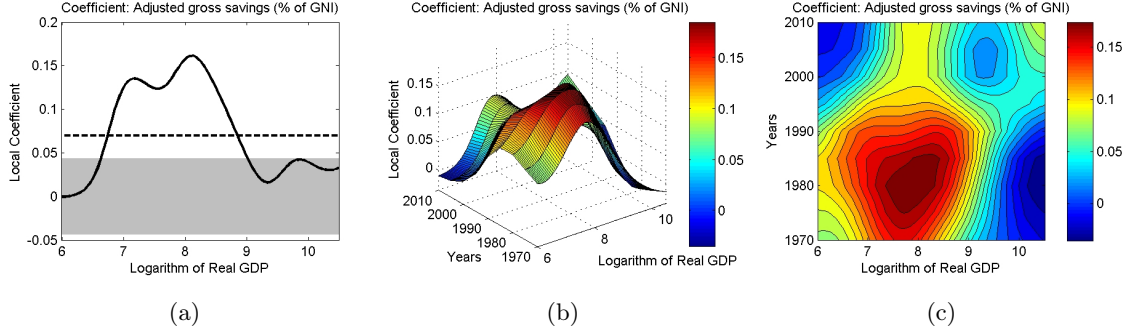


Figure 5: FCM estimates for rate of adjusted gross savings (% of GNI), $N=865$, 1965–2010. (a) 1-dim FCM estimate, (b) 2-dim FCM estimate as a surface plot, (c) same 2-dim FCM estimate as a contour plot. See sections 2.2.2 and 2.3.2 for a detailed description.

Average growth rates (in 5-year episodes) are regressed on a constant and the 5-year mean value of gross savings (equation 11).

$$g_{i,t} = \beta_0(u_{i,t}) + \beta_1(u_{i,t}) \cdot savings_{i,t} + \varepsilon_{i,t}. \quad (11)$$

Figures 5(a) through 5(c) depict functional coefficients for the gross savings rate over the the status variables support in a one-dimensional and two-dimensional setting. Functional estimates for the constant are left out due to space considerations, since the slope parameter is of primary interest. Observe that the functional estimate shows exactly the expected pronounced hump (Inverse-U) shape, thus confirming the considerations and results of *Aghion und Howitt (2006)*. The two-dimensional approach of Figures 5(b) and 5(c) shows that the expected hump shape is clearly visible over the whole sample period, even if the strength of the relationship appears to decrease since the mid-nineties.

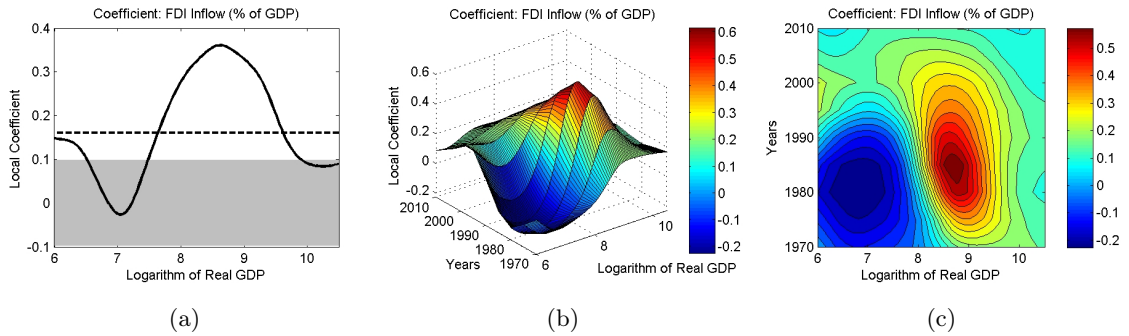


Figure 6: FCM estimates for FDI inflow, $N=1008$, 1965–2010. (a) 1-dim FCM estimate, (b) 2-dim FCM estimate as a surface plot, (c) same 2-dim FCM estimate as a contour plot. See sections 2.2.2 and 2.3.2 for a detailed description.

In an alternative model setup, we replace the savings rate by a direct measure of the relationship under investigation, i.e. the net inflow of foreign direct investments as a percentage of real GDP. That way, we obtain Figures 6(a) through 6(c) as functional coefficient estimates of FDI Inflow. Observe that the expected hump shape is clearly visible for the whole sample period, even if it becomes less pronounced since approximately 1995. For very rich countries as well as very

poor countries the influence of foreign direct investments on growth appears less present than for middle-income countries.

3.3 Macroeconomic and Demographic Measures

Figures 7(a) through 7(c) show that while the overall influence of higher government consumption seems to be negative, this relationship appears absent for very poor countries. Moreover, in recent years (2005-2010), the relationship seems to become even positive, especially in rich countries. This might be interpreted as an indication that counter-cyclical Keynesian policies during the world financial crisis have contributed to dampen output losses.

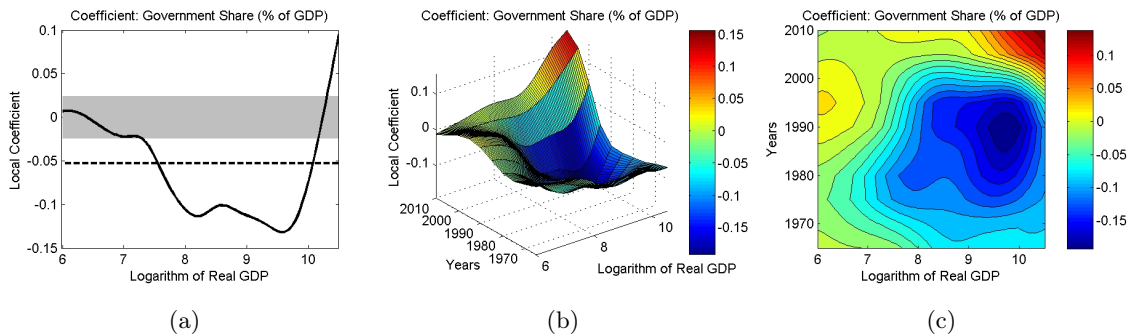


Figure 7: FCM estimates for government share (% of GDP), $N=1267$, 1960-2010. (a) 1-dim FCM estimate, (b) 2-dim FCM estimate as a surface plot, (c) same 2-dim FCM estimate as a contour plot. See sections 2.2.2 and 2.3.2 for a detailed description.

The dotted line in Figure 8(a) shows that there is a positive sign for merchandise trade (% of GDP) in a regular OLS growth regression, even if this result is not significant at 5% level. It also shows that the functional coefficient is turning strongly negative for very poor countries, while only middle-income countries seem to actually benefit from trade liberalization in a significant way. 8(b) through 8(c) show that the result for poor countries is not stable over time. Until the seventies, possibly due to fixed exchange rates in the *Bretton-Woods-System*, the coefficient of trade was strongly positive. Since 1980, the functional coefficient became negative, thus indicating that a higher trade share was accompanied by a very bad growth record in poor countries, at least on average. Poor open economies were probably unable to handle the uncertainty of flexible exchange rates as good as middle-income and developed economies. However, causality is not proven, so it is reasonable to remain careful.

Figures 9(a) through 9(c) show functional coefficients for a growth model with (a constant and) the old age dependency ratio, which is the population share aged 65 and older divided by the working age population (15-64 years). Functional estimates show that a positive effect of this variable on growth seems to be present for poor and middle-income countries, which may rather reflect a proxy variable for positive effects of good medical care. In rich economies, this positive effect on growth seems to be non-existent over the whole span from 1960 through 2010. In recent years, the relationship seems to have become even negative for high-income countries reflecting

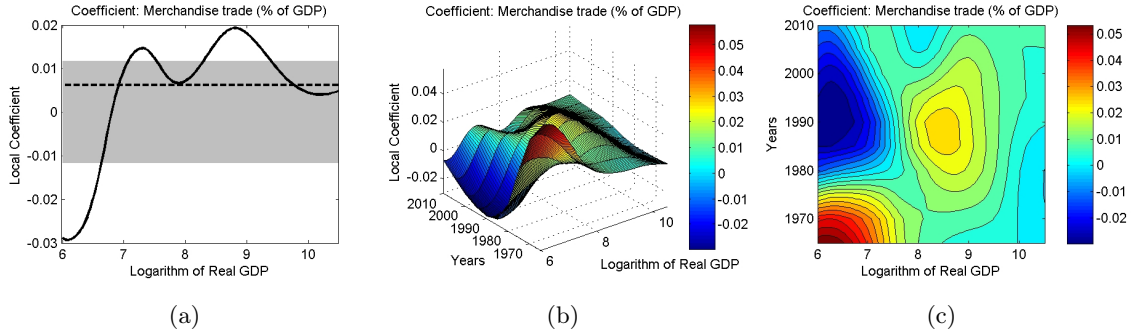


Figure 8: FCM estimates for share of merchandise trade (% of GDP), $N=1178$, 1960-2010. (a) 1-dim FCM estimate, (b) 2-dim FCM estimate as a surface plot, (c) same 2-dim FCM estimate as a contour plot. See sections 2.2.2 and 2.3.2 for a detailed description.

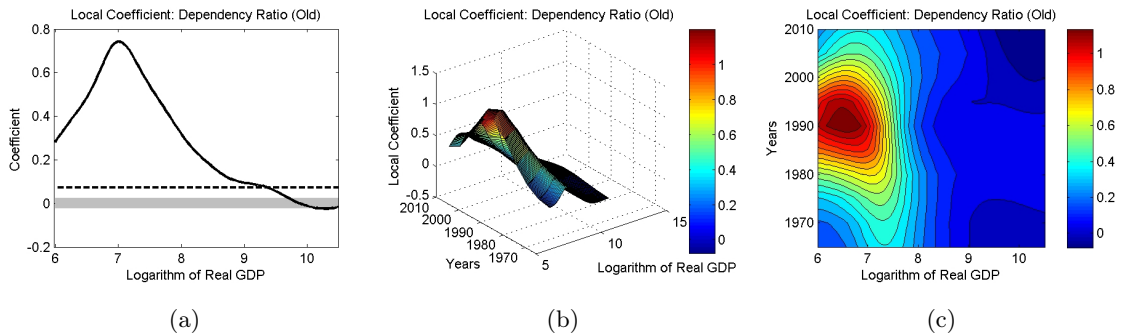


Figure 9: FCM estimates for old age dependency ratio, $N=1267$, 1960-2010. (a) 1-dim FCM estimate, (b) 2-dim FCM estimate as a surface plot, (c) same 2-dim FCM estimate as a contour plot. See sections 2.2.2 and 2.3.2 for a detailed description.

the demographic burden of aging societies.

It should be noted that not all variation in shown functional coefficients allows for an intuitively convincing interpretation. There is certainly a large degree of sensitivity of results to variations in the panel data set. However, even if a detailed interpretation of functional coefficient is not found reliable, there are clearly benefits from using this method, since it allows a closer investigation of heterogeneity. Similar to outlier analysis it is possible to determine whether overall results are driven systematically by a certain number of observations. In the context of growth regressions, the overall influence of a certain measure on growth may be driven by observations from a certain decade only, or by a group of very poor countries. Some generalized results may not be valid for a certain subgroup of countries. Running a functional coefficient approach may as well serve as a sensitivity analysis from which additional insights are gained. Similarly, if we are interested in the determination of a suitable subsample of a huge panel data set, that is, a subsample that allows to emphasize certain principles, the discussed method might be a helpful tool to accomplish this goal.

4 Functional and Constant Coefficients Combined

4.1 Prefiltering of Control Variables

Bivariate analysis of growth determinants from section 3 does not include any control variables. This could be viewed as a major shortcoming of previous analysis, since multiple regression allows to test explanatory variables competitively. One way to include control variables is given by the Frisch-Waugh-theorem (Greene, 2003), by which a multivariate model can be reduced via partial regression. The desired investigation of functional relationships with a single selected variable remains possible, while important control variables can also be included into the regression model.¹² By using a partial regression approach it is possible to filter out control variables with assumed constant coefficients.

If we are interested in a model setting where only a part β_2 of the explanatory variables' coefficients are characterized by functional dependence, which, in our case, is a constant and one additional slope parameter. The control variables' coefficients β_1 are assumed to be constant:

$$g_{i,t} = x1'_{i,t} \cdot \beta_1 + x2'_{i,t} \cdot \beta_2(u_{i,t}, w_{i,t}) + e_{i,t}. \quad (12)$$

In partial regression, the dependent variable and remaining explanatory variable(s) are regressed on the matrix of variables to be filtered out. Then, residuals of first stage regressions are used to proceed with local estimation.¹³

The *Solow* (1956) growth model provides three explanatory variables suitable as a core model. Initial GDP, investment and population growth are established theory-based variables that can be filtered out via partial least squares. Logarithm of real initial GDP per capita is included to account for the effect of convergence. The coefficient is found significantly negative in most studies (see *Levine and Renelt*, 1992). Investment is a measure for physical capital accumulation, whose coefficient is expected and usually found significantly positive. Population growth accounts for a growing workforce that needs to be endowed with physical capital. Moreover, child care is time-consuming, therefore high population growth is expected to reduce per capita growth. Thus, the expected sign is negative, while existing findings in the literature are rather mixed.¹⁴

¹²Functional coefficients for multivariate model specifications were not found robust. See section 3.1 for some reasoning.

¹³In a strictly linear case of partial regression, constant coefficients of x_1 can be computed afterwards by using the estimated residuals of first stage partial regression. Using that procedure in our case, i.e. using residuals from FCM regression to compute constant coefficients afterwards, a strictly linear least squares model would be mixed up with a highly nonlinear functional coefficient approach. That is why only functional coefficients are shown, but there are no reasonable estimates of the constant coefficients.

¹⁴Long-run growth in the *Solow* model is dependent only on an external rate of technological progress, so all three variables are expected to have no effect in the long run. In the short run, however, coefficients are expected to be of mentioned sign.

In the following, one variable at a time is added to the core model to investigate its functional dependence while controlling for mentioned three variables.

4.2 Selected Results

Figures 10(a) through 10(c) show results of a growth model containing a constant, initial GDP, investment (% of GDP), population growth and the share of government consumption (% of GDP). Initial GDP, investment and population growth, referred to as the core Solow model, are filtered out via mentioned Frisch-Vaugh theorem. The remaining variance of economic growth is then investigated closely for its functional dependence in one and two dimensions. Comparing the results to the model of bivariate relationships (Figures 7(a) through 7(c)) we see that its pattern is very similar. Including control variables did not change the functional dependence to a large extent.¹⁵ Again, results suggest that while the overall influence of higher government consumption seems to be negative, this relationship is absent for very poor countries. Moreover, in recent years, the relationship even seems to become positive in all development stages. A standard model of constant coefficients may claim to find a statistically significant negative influence of government consumption over the years 1960 through 2010, but FCM analysis shows how this finding is flawed for recent years.

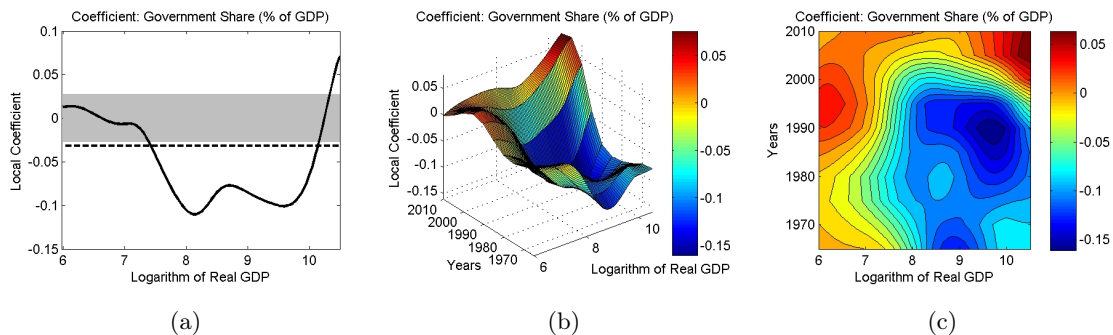


Figure 10: FCM estimates for government share (% of GDP), controlling for investment, population growth and initial GDP, $N=1253$, 1960-2010. (a) 1-dim FCM estimate, (b) 2-dim FCM estimate as a surface plot, (c) same 2-dim FCM estimate as a contour plot. See sections 2.2.2 and 2.3.2 for a detailed description.

Again, Figures 11(a) through 11(c) are comparable in shape to the bivariate case of Figures 8(a) through 8(c). Even if overall effect of merchandise trade appears to be unrelated to growth, FCM analysis shows that too much trade may be detrimental to poor countries' growth prospects, at least since approximately 1980. On the other hand, middle-income countries may benefit from larger trade shares.

Figures 12(a) through 12(c), compared with its bivariate counterparts of section 3.3 show some minor differences in detail, but qualitatively there is no big difference. The overall effect of a larger dependency ratio appears slightly positive, if anything, but this finding is only true for

¹⁵Note that the dotted line in Figure 7(a) is very close to the grey-shaded area compared to Figure 10(a). Therefore, the p-value for this coefficients OLS estimate in the multivariate model is closer to 0.05.

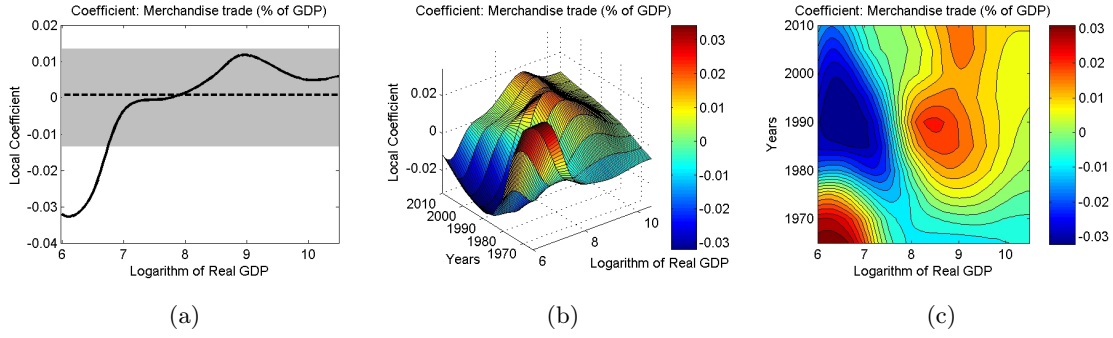


Figure 11: FCM estimates for share of merchandise trade (% of GDP), controlling for investment, population growth and initial GDP, $N=1166$, 1960-2010. (a) 1-dim FCM estimate, (b) 2-dim FCM estimate as a surface plot, (c) same 2-dim FCM estimate as a contour plot. See sections 2.2.2 and 2.3.2 for a detailed description.

poor countries (see Figure 12(a)). The reason is that a relatively large proportion of elderly people in a poor country reflects a good health care system to some extent, which is regarded as a prerequisite for growth. In high-income countries, there seems to be no effect until 1990. In latest years, however, a larger old age dependency ratio became a liability to growth prospects in those countries, reflected by negative local coefficients in the upper right corner of Figures 12(b) and 12(c).

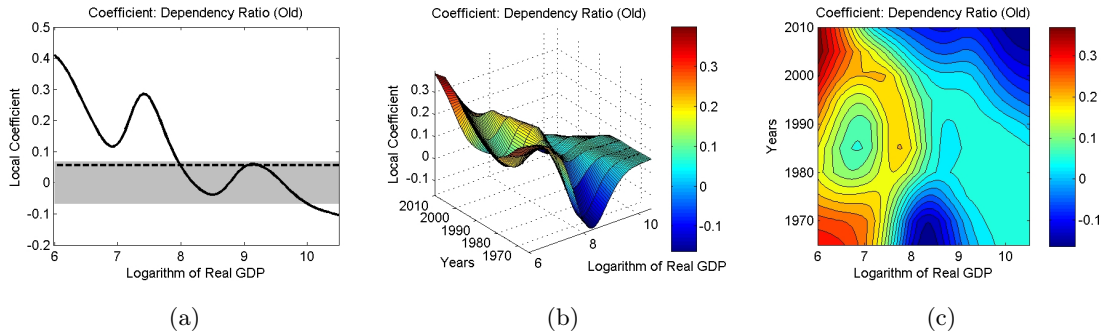


Figure 12: FCM estimates for old age dependency ratio, controlling for investment, population growth and initial GDP, $N=1253$, 1960-2010. (a) 1-dim FCM estimate, (b) 2-dim FCM estimate as a surface plot, (c) same 2-dim FCM estimate as a contour plot. See sections 2.2.2 and 2.3.2 for a detailed description.

Figures 13(a) through 13(c) are shown to provide rather counter-intuitive results. Combined with given control variables, this model is close to the augmented Solow model from Mankiw et al. (1992), featuring an education variable to account for human capital accumulation. Pooled OLS regression provides a statistically significant positive coefficient for tertiary school enrolment, which is depicted as dotted line in Figure 13(a). While this overall result appears convincing at first, Figure 13(a) shows that the coefficient is much higher in low-income countries, while tertiary education has no effect on growth in middle-income and developed, industrial countries. This appears rather counter-intuitive. Results of the two-dimensional model suggest that tertiary education is less but still important in middle-income and high-income countries when we only focus on the years 1985 and later. Before that time, the coefficient even turns negative.

How come that the results suggest tertiary schooling to play a more important role in poor

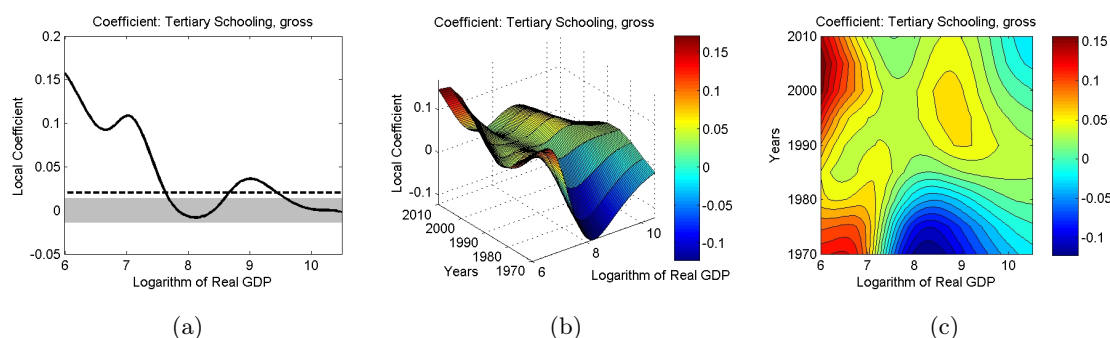


Figure 13: FCM estimates for tertiary school enrolment, controlling for investment, population growth and initial GDP, $N=1073$, 1965-2010. (a) 1-dim FCM estimate, (b) 2-dim FCM estimate as a surface plot, (c) same 2-dim FCM estimate as a contour plot. See sections 2.2.2 and 2.3.2 for a detailed description.

countries, while the coefficient declines with GDP level? A technical constraint of functional estimation emerges during a close investigation of results like this: Explanatory variables of FCM should not vary in their order of magnitude across the status variables' support. Otherwise, estimated local coefficients may also vary in their order of magnitude, which renders results highly questionable. In this case, tertiary school enrolment in low-income countries ranges on average between 2 and 3 per cent, while it ranges between 40 to 50 per cent in high-income countries (see figure 14(c)). Local estimation in an environment where most observations of the explanatory variable assume values of 2 or 3 per cent will result in much higher slope coefficients, compared to a local environment with an explanatory variable with values between 40 and 50 per cent, thus local coefficients in this case are not reliable. Therefore we need to be careful regarding the choice of explanatory variables. Questionable results may simply reflect a different order of magnitude of the explanatory variable at different positions of the status support. Figures Figure 14(a) and 14(b) show that local mean values of government share and old age dependency ratio vary to a lesser extent.

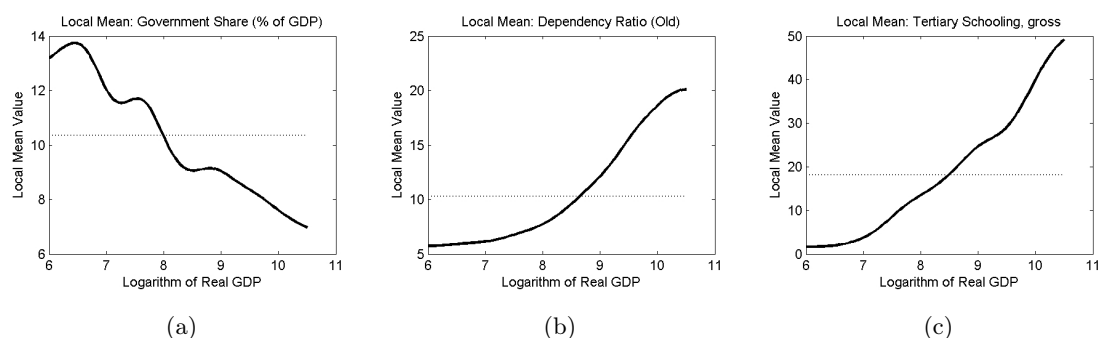


Figure 14: Local mean values for (a) Government share (% of GDP) (b) Old age dependency ratio, (c) Tertiary school enrolment. See section 2.2.3 for a detailed description.

5 Spin-Off: Contours of Development

By using the weighting scheme from functional estimation, we are able to compute local mean values dependent on status variables. Note that this procedure is identical to regressing the variable of interest $y_{i,t}$ on a mere constant along the support of the status variables $u_{i,t}$ and $w_{i,t}$ using FCM. Local mean values in a two-dimensional setting at position \bar{u} and \bar{w} are computed according to:¹⁶

$$\bar{y}_{..}^{local}(\bar{u}, \bar{w}) = \frac{\sum_{i=1}^N \sum_{t=1}^T y_{i,t} \cdot K_{u,h}(u_{i,t} - \bar{u}) \cdot K_{t,h}(w_{i,t} - \bar{w})}{\sum_{i=1}^N \sum_{t=1}^T K_{u,h}(u_{i,t} - \bar{u}) \cdot K_{t,h}(w_{i,t} - \bar{w})} \quad (13)$$

Contour plots of resulting local mean values across time and GDP levels provide a colourful visualisation of worldwide economic and demographic development along two dimensions. Figure 15 is one example of how fertility (children per woman) ranges between rich and poor countries over time.

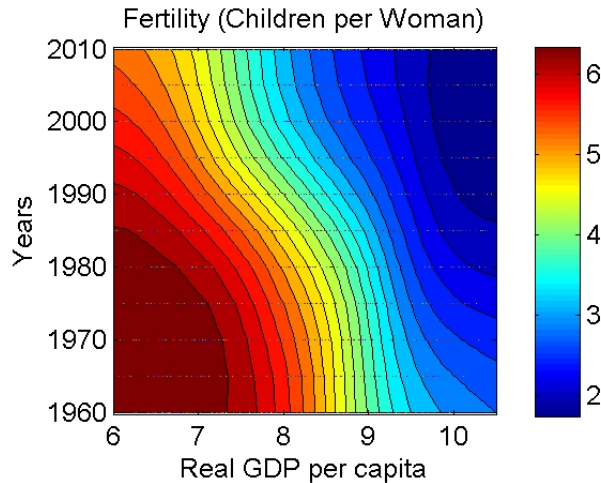


Figure 15: Contour plot of local mean values for 5-year fertility average, N=1607.

In order to provide additional information about observation density across the status support, each observation is marked in the two-dimensional contour plot, as is done in figure 15. Due to worldwide economic growth over the decades, observation marks are moving slightly to the right from 1960 through 2010. Observe isoquants are moving from top-left to bottom-right indicating that fertility has reduced for all income-levels over the years. In the richest economies, average fertility has reduced from approximately 3 to less than 2 children per woman, fertility in least developed countries declined from 6.5 to slightly more than 5 in recent years.

¹⁶See section 2.2.3 for comparison with one-dimensional local mean value and its description. Notation is in accordance with earlier chapters.

Selected Examples

Now that visualisation of local mean values is explained, additional examples are shown in subsequent diagrams. Figure 16(a) features isoquants sloping downwards from top-left to bottom-right. This indicates that trade intensity has increased worldwide between 1960 and 2010, either in low-income, middle-income or in high-income countries. Moreover, trade intensity seems to be proportional to GDP level: Looking from left to right there is a rise in local means over the whole time span. The same findings are valid for life expectancy at birth (Figure 16(b)), but here the isoquants are steeper. Local mean values of life expectancy have increased about ten years for all per capita income levels, but the difference between poorest and richest countries is even larger. Local mean values in high-income countries moved approximately from 67 to 77 years, while poorest countries' local mean moved from roughly 45 to 55 years.

Figures 16(c) and 16(d) provide some insights regarding educational attainment. Adult Literacy has been rising in all countries, but more so in poor and middle-income countries. By looking at literacy rates as a single indicator, it appears that the gap between high-income countries and the rest of the world has been narrowed over the years. Looking at tertiary school enrolment in Figure 16(d) as another indicator, downward sloping isoquants indicate a rise over all income-levels again. However, in this case the increase has been much larger for high-income countries. Therefore, this alternative indicator of educational attainment implies that the gap between rich and poor countries regarding higher education has widened.

Figure 16(e) shows that the stock of migrants is much higher and growing in high-income countries. Not surprisingly, high-income countries appear more attractive than low- and middle-income countries when people choose to migrate. The migration stock in poor and middle-income countries has been reduced over the years. Finally, Figure 16(f) depicts local mean values of HIV prevalence between 1990 and 2010. It appears that a maximum of infections has been recorded around the year 2000 in low-income countries. Since then, HIV casualties outweighed new infections such that the HIV prevalence in the population was reduced for the group of very poor countries. On the other hand, ascending isoquants for middle-income and richer countries suggest that overall prevalence of HIV has sharply increased over time, even if average percentage levels for all income-levels remain below 4 per cent, in high-income countries even below 1 per cent. Note that these are only average levels of whole countries.

The presented local mean procedure offers a new way to visualize panel data. It allows to investigate worldwide developments in demographic, macroeconomic and financial measures in a two-dimensional diagram.

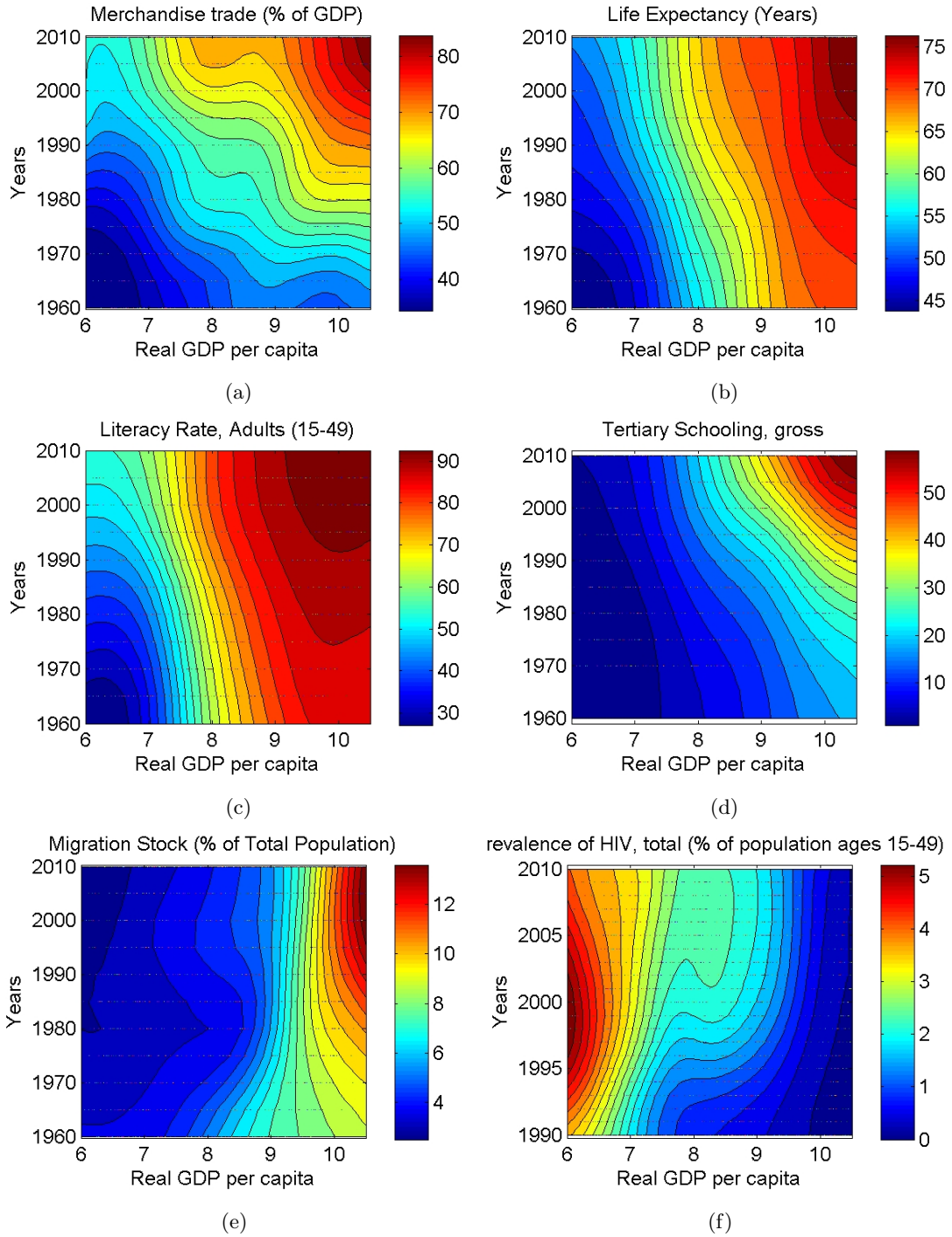


Figure 16: Contour plot of local mean values for (a) Trade share, $N=1463$, (b) Life expectancy at birth, $N=1608$, (c) Literacy rate of population (ages 15-49), $N=675$, (d) tertiary school enrollment ratio, $N=1216$, (e) Migration stock (% of total population), $N=1668$, (f) HIV prevalence (% of population ages 15-49), $N=2709$.

6 Conclusion

This paper applies functional coefficient analysis in the field of cross-country growth regressions. A panel data set of 145 countries between 1960 and 2010 was used, while focusing on medium-

run growth dynamics. Functional coefficients were determined in a one-dimensional FCM with initial GDP as a status variable; and also in a two-dimensional FCM using the time dimension as a second status variable. Valuable insights can be generated from visualizations of functional coefficients of both models.

Instead of applying FCM to large multivariate models, whose results could hardly be considered robust, it was applied for the detailed investigation of bivariate relationships of economic growth. So the relationship of per capita growth rates with one variable at a time was investigated, namely investment, gross savings, foreign direct investment, government consumption, trade intensity, old age dependency ratio and tertiary educational attainment. For comparison, prefiltering of growth rates allowed to take established control variables of the *Solow* model into consideration. Estimated functional coefficients were qualitatively very similar to the bivariate case. In the light of given results, showing that locally estimated coefficients of growth determinants indeed vary strongly over time and also between poor and rich countries, it appears highly questionable to simply assume parameters to be constant as it is done in a standard growth regression.

Moreover, modeling economic relationships with functional coefficients allows a closer investigation of heterogeneity. It is possible to determine whether results of a constant coefficient model are primarily driven by a certain number of observations. The overall influence of a certain measure on a dependent variable may be strongly influenced by observations from a certain time period only, or by a subgroup of countries, while generalisation of the finding for the whole data set may be invalid. Hence, FCM may as well provide a sensitivity analysis and robustness check for OLS regression models in general.

As a spin-off, local mean values are generated if FCM is applied to a variable of interest without explanatory variables but a constant, that is dependent on two status variables. By computing local mean values across the support of both status variables and putting them into a contour plot, a colourful diagram of macroeconomic or demographic panel data is generated. The result is a descriptive statistic, useful for example in the field of development economics.

References

- [1] Aghion, P., Howitt, P. (2006), Appropriate Growth Policy: A Unifying Framework. *Journal of the European Economic Association*, 4 (2/3), 269–314.
- [2] Baltagi, B. (2005), *Econometric Analysis of Panel Data*, 3rd ed., Chichester.
- [3] Cai, Z., Fan, J. und Yao, Q. (2000), Functional Coefficient Regression Models for Nonlinear Time Series. *Journal of the American Statistical Association* 95, 941–956.
- [4] Durlauf, S.N. and Johnson, P.A. (1995), Multiple regimes and cross-country growth behaviour. *Journal of Applied Econometrics* 10, 365–384.
- [5] Durlauf, S.N., Kourtellos, A., Minkin, A. (2001), The local Solow growth model. *The European Economic review* 45, 928–940.
- [6] Durlauf, S.N., Johnson, P.A., Temple, J. (2005), Growth econometrics, in: Aghion, P., Durlauf, S.N. (2005), *Handbook of economic growth*, Amsterdam, 555–677.
- [7] Jennen-Steinmetz, C. and Gasser, T. (1988). A unifying approach to nonparametric regression estimation. *Journal of the American Statistical Association* 83, 1084–1089.
- [8] Greene, W.H. (2003), *Econometric Analysis*, 5th ed., London.
- [9] Härdle, W., Müller, M., Sperlich, S., Werwatz, A. (2004), *Nonparametric and semiparametric models*. Berlin.
- [10] Henderson, D. J., Papageorgiou, C. and Parmeter, C. F. (2012), Growth Empirics without Parameters. *The Economic Journal* 122, 125–154.
- [11] Herwartz, H. und Xu, F. (2007), A New Look at the Feldstein-Horioka Puzzle, University of Kiel, *Economics working paper* 2007–14.
- [12] Heston, A., Summers, R. and Aten, B. (2012), Penn World Table Version 7.1, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania, July 2012.
- [13] Hodrick, R.J., Prescott, E.C. (1997), Postwar U.S. Business Cycles: An Empirical Investigation. *Journal of Money, Credit and Banking* 29, 1–16.
- [14] Ketteni, E., Mamuneas, T.P. and Stengos, T. (2007), Nonlinearities in economic growth: A semiparametric approach applied to information technology data. *Journal of Macroeconomics* 29 (3), 555–568.
- [15] Kourtellos, A. (2002), Modeling Parameter Heterogeneity in Cross Country Growth Regression Models. University of Cyprus Discussion Paper 2002–12.
- [16] Levine, R., Renelt, D. (1992), A Sensitivity Analysis of Cross-Country Growth Regressions. *American Economic Review* 82 (4), 942–963.

- [17] Liu, Z. and Stengos, T. (1999), Non-linearities in cross-country growth regressions: a semi-parametric approach. *Journal of Applied Econometrics* 14, 527–538.
- [18] Lucas, R. (1988), On the Mechanics of Economic Development. *Journal of Monetary Economics* 22, 3–42.
- [19] Mamuneas, T.P., Savides, A. and Stengos, T. (2006). Economic development and the return to human capital: a smooth coefficient semiparametric approach. *Journal of Applied Econometrics* 21 (1), 111–132.
- [20] Mankiw, N. G., Romer, D., and Weil, D. N. (1992). A Contribution to the empirics of economic growth. *Quarterly Journal of Economics* 107 (2), 407–437.
- [21] McCartney, M. (2006), Can a Heterodox Economist Use Cross-Country Growth Regressions? *Real-world economics review* 37, 45–54.
- [22] Nadaraya, E. (1964), On Estimating Regression. *Theory of Probability and its Applications* 10, 186–190.
- [23] Romer, P.M. (1986), Increasing Returns and Long-Run Growth. *Journal of Political Economy* 94, 1002–1037.
- [24] Romer, P.M. (1990), Endogenous Technological Change. *Journal of Political Economy* 99, 71–102.
- [25] Sala-i-Martin, X., Artadi, E. (2004), The Global Competitiveness Index, in: Porter, M. et al. (Hrsg.), *The Global Competitiveness Report, 2004-2005*, Oxford University Press.
- [26] Snowdon, B. (2006), The Enduring Elixir of Economic Growth. Xavier Sala-i-Martin on the Wealth and Poverty of Nations. *World Economics* 7 (1), 73–130.
- [27] Solow, R.M. (1956), A contribution to the Theory of Economic Growth. *Quarterly Journal of Economics* 70, 5–94.
- [28] Vaona, A., Schiavo, S. (2007). Nonparametric and semiparametric evidence on the long-run effects of inflation on growth. *Economic Letters* 94 (3), 452–458.
- [29] Watson, G. (1964), Smooth Regression Analysis. *Sankhya: The Indian Journal of Statistics* A 26, 359–372.
- [30] World Bank (2012), *World Development Indicators 2012*, Washington, DC. Link: <http://data.worldbank.org/data-catalog/world-development-indicators>.