



IIASA

International Institute for
Applied Systems Analysis
Schlossplatz 1
A-2361 Laxenburg, Austria

Tel: +43 2236 807 342
Fax: +43 2236 71313
E-mail: publications@iiasa.ac.at
Web: www.iiasa.ac.at

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Human Capital, Age Structure and Growth Fluctuation

Jesús Crespo Cuaresma (jesus.crespo-cuaresma@uibk.ac.at)
Tapas Mishra (mishra@iiasa.ac.at)

Approved by

Wolfgang Lutz (lutz@iiasa.ac.at)
Leader, World Population Program

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Abstract

This paper assesses empirically the relationship between GDP per capita growth fluctuations and the age structure and intensity of human capital across developed and developing countries. We estimate a spatial vector autoregressive model of income dynamics where the economic distance between countries is defined on their similarity in measures of human capital and its distribution across age groups. These distances are computed using a newly developed human capital data set. Spatial effects on growth volatility and complementarity in national growth processes are explored with respect to the proposed distance metrics. Our results imply that significant growth interdependence based on human capital distances exists among countries, with highly non-linear effects.

Key words: Economic growth, fluctuations, spatial vector autoregression, human capital, demographic structure.

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About the Authors

Jesús Crespo Cuaresma is the Leader of the Project on Human Capital and Economic Growth within the World Population Program at IIASA, and Professor of Economics at the University of Innsbruck, Austria. E-mail: jesus.crespo-cuaresma@uibk.ac.at

Tapas Mishra is a Post-Doctoral Research Scholar with the World Population Program at IIASA. E-mail: mishra@iiasa.ac.at

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1 Introduction

The importance of human capital as a determinant of economic growth has been extensively studied in the theoretical and empirical economic literature. The potential channels through which education affects economic growth have been traditionally modeled in two different (not necessarily exclusive) ways. On the one hand, human capital has been included as an additional factor of production in economic models based on a production function approach (see the seminal contributions by Lucas 1988; Mankiw *et al.* 1992; Hall and Jones 1999). On the other hand, the difficulties reported in empirical applications in finding a robust correlation between additions to the human capital stock and growth in GDP per capita have led other authors to rely on the Nelson and Phelps (1966) paradigm and model human capital as a variable that affects the creation and adoption of new technologies (and therefore tends to be included as a determinant of total factor productivity), instead of a traditional input of production. Benhabib and Spiegel (1994, 2005) are excellent examples of this branch of research.

Although the research carried out in this direction has been able to shed light on the role of human capital as a determinant of growth, practically no research has been carried out, to the knowledge of the authors, on the role of human capital in the transmission of productivity shocks (and thus as a determinant of common growth fluctuations) across countries. The leading theories of economic fluctuations (real business cycles and new Keynesian models) invariably require large, persistent, aggregate shocks in order to generate realistic business cycles. Yet, research so far has produced scant evidence of the existence or empirical relevance of such shocks. The failure to identify suitable aggregate shocks has led to a renewal of interest in alternative sources of fluctuations. Following the suggestions of Long and Plosser (1983) several researchers have investigated whether and under what conditions small idiosyncratic shocks that operate at the sectoral, firm or individual country level may not cancel out in the aggregate but build up to produce aggregate effects. Such implications may arise due to the interconnectedness of sectors. For instance, idiosyncratic shocks may exhibit a high degree of synchronization due, for example, to Marshallian externalities or to spillovers.

Horvath (1998, 2000) shows that independent individual country specific shocks may induce large aggregate fluctuations when trade among countries is characterized by a lack of substitutability in each country's inputs (human capital may thus be deemed as one of the factors playing a role here). On the other hand, similarity in the size and distribution of the human capital stock across economies may be an important factor of propagation of shocks whose source is endogenous technology improvements. In particular, the interplay between age structure of the population and education has been shown to be relevant in the adoption of technology, par-

ticularly for relatively developed economies (see Crespo Cuaresma and Lutz 2007). Considering the similarity in the distribution of human capital among different economies (thus in a spatial frame) can thus help us characterize ‘common’ behavior in the fluctuations of income growth in different countries.

Positive (negative) spatial growth correlation has immediate implications for the ‘complementarity theory’: a unit increase in growth in one location increases (decreases) the growth return in another location. The high degree of correlation may have to do with the high integration of economies across borders due to the increasing relaxation of trade barriers, for instance. Therefore, in the strict sense of the term, when a spatial structure is assumed, no single economy is independent of the development occurring elsewhere, at least in the neighborhood. Proximity does matter, whether it is in the relational or geographic sense: Everything is related to everything else, but near things are more related than distant things (Tobler 1970).

There is recent empirical evidence on the fact that distance measures based on demographic patterns define spatial relationships that imply significant cross-country links in the growth process. Azomahou and Mishra (2007) and Azomahou *et al.* (2007) show that countries sharing common demographic features tend to generate growth synergies. In this context, considering (potentially age-structured) human capital as the variable in which to root the distance measure may shed a light on the nature of such linkages. Feedback effects may occur from human capital to demographic system and vice versa, most probably with a time lag. High growth of human capital (educated mass) would most likely affect the level of demographic change, while the speed of the latter also will determine the rate of human capital accumulation at a later stage. Since human capital developments have a spatial character (due to the adoption of similar educational policy, for instance), the induced demographic change could also share this spatial similarity. A myriad of implications and economic policy concerns are naturally related to this view of interrelations across countries. Once the link binding countries together is found, can joint policy management in those countries retain national welfare and promote global welfare? Should countries cooperate in growth-policy management because their growths are correlated?

In this contribution we assess empirically the role of human capital and its age structure as a determinant of common growth fluctuations. In particular, we use a spatial vector autoregressive panel model to estimate the effects of human capital accumulation on per capita growth variations in different groups of countries. We adopt Chen and Conley’s (2001) non-parametric approach to modeling spatial vector autoregressions in a panel setting. By employing this method, the interrelation between countries can be captured in two ways. First, like in a vector autoregression, the growth rate of each country is affected by the (past) growth rates of all other countries in the sample. Second, we can model the covariances of the error terms as a function of economic distance, based on a metric which relates to the importance and distribution of human capital. We use a non-parametric estimation method for spatial dependence, which therefore does not depend upon a specific functional form. Different metrics can be used to accommodate human capital as a determinant of shock correlations in a spatial setting.

The paper is structured as follows. In Section 2 the econometric model is presented. Section 3 presents and discusses the data and distance definitions used in the analysis. Section 4 presents empirical results for different distance measures and different groups of countries, and Section 5 concludes.

2 The Econometric Model

Our econometric specification embodies a dynamic structure in the form of a panel vector autoregressive (VAR) model on growth rates of GDP per capita, where the structure of the error term allows for a general type of spatial correlation across countries. This setting allows us to quantify the effect of *human capital distance* on the diffusion of shocks to GDP per capita among countries in the sample. The econometric specification and the estimation method used are based on Chen and Conley (2001) and Conley and Dupor (2003). The model is characterized by spatio-temporal links in the process of economic growth, where the spatial dimension is based on a distance measure constructed using human capital data. The results for different potential measures of human capital distance, which were computed using a new data set that comprises information on demographic structure and educational attainment across countries of the world, are reported below.

2.1 A spatial VAR growth model

We describe economic growth in a semiparametric spatial VAR framework. Let $\{Y_{i,t} : i = 1, \dots, N; t = 1, \dots, T\}$ denote the sample realizations of the growth variable for N countries at locations $\{s_{i,t} : i = 1, \dots, N; t = 1, \dots, T\}$. Now, let \mathbf{D}_t be a stacked vector of distances between the $\{s_{i,t}\}_{i=1}^N$ defined for two points i and j as $\mathbf{D}_t(i, j) = \|s_{i,t}, s_{j,t}\|$ with $\|\cdot\|$ denoting the Euclidean norm. Then,

$$\mathbf{D}_t = [D_t(1, 2), \dots, D_t(1, N), D_t(2, 3), \dots, D_t(2, N), D_t(N-1, N)]' \in \mathbb{R}^{\frac{N(N-1)}{2}}$$

Moreover, the distances are assumed to have a common support $(0, d_{\max}]$ for all $t, i \neq j$. We assume that the growth of a given country denoted at $t+1$ denoted $Y_{i,t+1}$ will depend not only on its own past (home externalities), but also nonparametrically on the performance of its neighbors (spatial spillovers effects). Given the history $\{Y_{t-l}, D_{t-l}, l \geq 0\}$, our specification is given by

$$Y_{i,t+1} = \alpha_i Y_{i,t} + \sum_{j \neq i}^N f_i(\mathbf{D}_t(i, j)) Y_{j,t} \quad (1)$$

where the α_i parameters describe the strength of externalities generated by home growth, f_i are continuous functions of distances mapping from $(0, \infty)$ to \mathbb{R}^l . One interesting feature in this specification is that it does not assume an a-priori parametric specification of neighborhood structure as usually done in parametric spatial models.

Let us denote $\mathbf{Z}_t = (Y_{1,t}, Y_{2,t}, \dots, Y_{N,t})' \in \mathbb{R}^N$ as a vector stacking $\{Y_{i,t}\}_{i=1}^N$. Following Chen and Conley (2001), we model the joint process $\{(\mathbf{Z}_t, \mathbf{D}_t) : t = 1, \dots, T\}$ as a first order Markov process which designs the evolution of \mathbf{Z}_t according to the following nonlinear Spatial Vector Autoregressive Model (SVAR):

$$\mathbf{Z}_{t+1} = A(\mathbf{D}_t)\mathbf{Z}_t + \varepsilon_{t+1}, \quad \varepsilon_{t+1} = Q(\mathbf{D}_t)\mathbf{u}_{t+1} \quad (2)$$

where $A(\mathbf{D}_t)$ is a $N \times N$ matrix whose elements are functions of human capital distances between countries. We assume that \mathbf{u}_{t+1} is an i.i.d. sequence with $\mathbb{E}(\mathbf{u}_{t+1}) = 0$ and $\mathbb{V}(\mathbf{u}_{t+1}) = I_N$. It follows that the conditional covariance matrix of ε_{t+1} is $\mathbb{E}(\varepsilon_{t+1}\varepsilon'_{t+1}) = Q(\mathbf{D}_t)Q(\mathbf{D}_t)' := \Omega(\mathbf{D}_t)$ which is also a function of distances. In the specification (2), the conditional mean $A(\mathbf{D}_t)$ and the conditional covariance $\Omega(\mathbf{D}_t)$ are of importance and have to be estimated. More structure will be imposed on these objects in order to allow estimation.

1. *Structure on conditional means.*

From (2), the conditional mean of $Y_{i,t+1}$ given $\{\mathbf{Z}_{t-l}, \mathbf{D}_{t-l}, l \geq 0\}$ is modeled as

$$\mathbb{E}[Y_{i,t+1} | \{\mathbf{Z}_{t-l}, \mathbf{D}_{t-l}, l \geq 0\}] = \alpha_i Y_{i,t} + \sum_{j \neq i}^N f_i(\mathbf{D}_t(i, j)) Y_{j,t} \quad (3)$$

where as pointed out above, the f_i are continuous functions mapping from $(0, \infty)$ to \mathbb{R}^l . Notice that this conditional mean turns out to be relation (3). As a result, it follows that the conditional mean of \mathbf{Z}_{t+1} given $\{\mathbf{Z}_{t-l}, \mathbf{D}_{t-l}, l \geq 0\}$ is $A(\mathbf{D}_t)\mathbf{Z}_t$

$$A(\mathbf{D}_t) = \begin{pmatrix} \alpha_1 & f_1(\mathbf{D}_t(1, 2)) & \cdots & f_1(\mathbf{D}_t(1, N)) \\ f_2(\mathbf{D}_t(2, 1)) & \alpha_2 & \cdots & f_2(\mathbf{D}_t(2, N)) \\ \vdots & \vdots & \ddots & \vdots \\ f_N(\mathbf{D}_t(N, 1)) & f_N(\mathbf{D}_t(N, 2)) & \cdots & \alpha_N \end{pmatrix} \quad (4)$$

It can be interesting in practice to model the α_i parameters and the f_i functions as having features in common across i .

2. *Structure on conditional covariances.*

The conditional covariance of \mathbf{Z}_{t+1} given $\{\mathbf{Z}_{t-l}, \mathbf{D}_{t-l}, l \geq 0\}$ is modeled as

$$\Omega(\mathbf{D}_t) = \begin{pmatrix} \sigma_1^2 + \gamma(0) & \gamma(\mathbf{D}_t(1, 2)) & \cdots & \gamma(\mathbf{D}_t(1, N)) \\ \gamma(\mathbf{D}_t(2, 1)) & \sigma_2^2 + \gamma(0) & \cdots & \gamma(\mathbf{D}_t(2, N)) \\ \vdots & \vdots & \ddots & \vdots \\ \gamma(\mathbf{D}_t(N, 1)) & \gamma(\mathbf{D}_t(N, 2)) & \cdots & \sigma_N^2 + \gamma(0) \end{pmatrix} \quad (5)$$

where $\gamma(\cdot)$ is assumed to be continuous at zero and is k -dimensional isotropic covariance function.¹ The choice of γ ensures that $\Omega(\mathbf{D}_t)$ is positive definite for any set of interpoint distance \mathbf{D}_t and any values of the $\sigma_i^2 \geq 0$. Yaglom (1987: 353–354) showed that an isotropic covariance function has a representation as an integral of a generalized Bessel function. The representation of γ is analogous to the spectral representation of time-series covariance functions.

2.2 Estimation strategy

For simplicity, we assume that the distance function \mathbf{D}_t is exogenous, i.e., determined outside the relation (2). We are interested in the shape of functions f_i and γ specified above. Chen and Conley (2001) propose a semiparametric approach based on the cardinal B-spline sieve method. This approach uses a flexible sequence of parametric families to approximate the true unknown functions. The cardinal B-spline of order m , B_m , on compact support $[0, m]$ is defined as

$$B_m = \frac{1}{(m-1)!} \sum_{k=0}^m (-1)^k \binom{m}{k} [\max(0, x-k)]^{m-1} \quad (6)$$

Hence, $B_m(x)$ is a piecewise polynomial of the highest degree $m-1$. Then, the functions of interest f_i and Φ can be approximated by

$$f_i(y) \approx \sum_{j=-\infty}^{\infty} a_j B_m(2^n y - j) \quad (7)$$

¹Isotropy means that the stationary random field (with indices in \mathbb{R}^k) that generates the process is directionally invariant.

and

$$\Phi(y) \approx \sum_{j=-\infty}^{\infty} b_j B_m(2^n y - j) \quad (8)$$

where the index j is a translation and the index n provides a scale refinement. The coefficients a_j and b_j are allowed to differ across these approximations. As n gets larger more $B_m(2^n y - j)$ are allowed and this in turn improved the approximation. Moreover, since B_m is nonnegative, a nondecreasing and nonnegative approximation of Φ can be obtained by restricting the coefficients b_j to be nondecreasing and nonnegative.

The estimation is performed in two-steps sieve least squares. In the first step, LS estimation of α_i and f_i , $i = 1, \dots, N$ is based on conditional mean (4) and sieve for f_i using the minimizations problem

$$\left(\hat{\alpha}_{i,T}, \hat{f}_{i,T} \right) = \arg \min_{(\alpha_i, f_i) \in \mathbb{R} \times \mathcal{F}_{i,T}} \frac{1}{T} \sum_{t=1}^T \left\{ Y_{i,t+1} - \left(\alpha_i Y_{i,t} + \sum_{j \neq i} f_i(\mathbf{D}_t(i, j)) Y_{j,t} \right) \right\}^2 \quad (9)$$

where $\mathcal{F}_{i,T}$ denotes the sieve for f_i (see Chen and Conley, 2001). Let us denote $\hat{\varepsilon}_{i,t+1} = (\hat{\varepsilon}_{1,t+1}, \dots, \hat{\varepsilon}_{N,t+1})$ the LS residuals following from the first stage:

$$\hat{\varepsilon}_{i,t+1} = Y_{i,t+1} - \left(\hat{\alpha}_{i,T} Y_{i,t} + \sum_{j \neq i} \hat{f}_{i,T}(\mathbf{D}_t(i, j)) Y_{j,t} \right) \quad (10)$$

Then, in the second step, sieve estimation for σ^2 and $\gamma(\cdot)$ based on the conditional variance (5), sieve for γ and fitted residuals $\hat{\varepsilon}_{i,t+1}$ is obtained as

$$\left(\hat{\sigma}_T^2, \hat{\gamma}_T \right) = \arg \min_{(\sigma^2, \gamma) \in (0, \infty)^N \times \mathcal{G}_T} \sum_{t=1}^{T-1} \left\{ \sum_i [\hat{\varepsilon}_{i,t+1}^2 - (\sigma_i^2 + \gamma(0))]^2 + \sum_i \sum_{i \neq j} [\hat{\varepsilon}_{i,t+1} \hat{\varepsilon}_{j,t+1} - \gamma(\mathbf{D}_t(i, j))]^2 \right\} \quad (11)$$

where \mathcal{G}_T denotes the sieve for γ . Chen and Conley (2001) derived the \sqrt{T} limiting normal distributions for the parametric components of the model. The authors also suggested a bootstrap method for inference as the pointwise distribution result for the nonparametric estimators \hat{f} and $\hat{\gamma}$ is not provided. Moreover, the asymptotic covariances are computationally demanding.

The model proposed above is estimated using data on GDP per capita growth as the Y_{it} variable and measures of the demographic distribution of human capital in order to specify the locations $s_{i,t}$. This allows us to assess and quantify the effect of (di)similarity in the demographic distribution of human capital on the transmission of shocks to income across countries. It should be noticed that this nonparametric approach is a departure from typical spatial econometric models in which a parametric form of dependence is assumed (see, e.g., Anselin and Griffith 1988 or Case 1991). The spatial model as described above puts restrictions on comovement across countries that are different from those of typical factor models. In this case, the covariance across variables is mediated by a relatively low dimensional set of factors as in, for example, Quah and Sargent (1993) and Forni and Reichlin (1998).

3 Data and Distance Definitions

The real GDP per capita series, measured in thousand constant dollars in 2001 international prices, are extracted from the *Penn World Table Version 6.2* (Heston *et al.* 2006), while the

age-structured human capital data is sourced from IIASA-VID (see Lutz *et al.* 2007a, 2007b). The time frame is 1970-2000 with annual frequency in all cases.

Some specific characteristics of the educational attainment data are in order. This human capital data set was produced in a joint effort by the International Institute for Applied Systems Analysis (IIASA) and the Vienna Institute of Demography (VID) and improves enormously on previously available data on education in several respects. In contrast to most earlier attempts to improve data quality, which were concentrated on raising more empirical information or using economic perpetual inventory methods and interpolation, such as the contributions of, for example, Barro and Lee (2001), de la Fuente and Domenech (2006) or Cohen and Soto (2001), this latest attempt is based on demographic back-projections and exploits for the first time differences in mortality across education levels.² Most importantly, this data set allows a cross-classification of education data by age groups (in age intervals of five years), and thus allows us to obtain estimates of the full demographic distribution of educational attainment.³

As compared to the existing datasets by Barro and Lee, De la Fuente and Domenech as well as Cohen and Soto, the IIASA-VID data reflect explicitly the fact that mortality differs by level of education and have education categories that are consistent over time. The dataset also provides the full educational attainment distribution by five-year age groups. Indeed, most economic growth regressions so far approximated human capital by one variable giving the mean years of schooling of the population above age 25. This indicator includes all elderly people beyond retirement age and therefore shows a much slower pace of improving average human capital than age-specific indicators for younger adults. In addition, the full distribution of educational attainment categories by age allows for important empirical studies about the relative importance of primary education as compared to secondary and tertiary in the course of development.

Two types of human capital distance measures have been used in this study: The first distance measure is based on the secondary education attainment level of the age-structured population for males, females and total population. Distances are defined as the Euclidean distance between country locations which are in turn defined as vectors in \mathbb{R}^3 whose elements are the average proportions of population in an age group (three age groups are considered: 14-29, 30-49 and 50-64) with completed secondary education. The second measure of economic distance is based on country-specific elasticities of economic growth to human capital, which is calculated by estimating a standard Cobb-Douglas production function where human and physical capital are used as inputs. The estimates were obtained from a pooled data set of five-year averages by regressing the growth rate of GDP per capita on the average investment rate, the change in years of education for the adult population and the initial level of GDP per capita (the education data is sourced from IIASA-VID and the rest of the variables are from the *Penn World Table Version 6.2*). Country-specific estimates of the parameter attached to the human capital variable were then used as elasticities in the construction of the distance matrix.

Based on the contiguity matrix of economic distance, we estimate a SVAR model to infer on complementarities in growth, their nature of interdependence and trace the source of fluctuations (in our case differences in the human capital accumulation in different countries). The list of countries in each group (namely, Asia, Africa, Europe, and Latin America and Offshore) is described in Table 1. The number of countries comprising each group complies with our

²The importance of these mortality differentials is highlighted by Cohen and Soto (2001), for instance. For a detailed description of the methodology used to reconstruct the data see Lutz *et al.* (2007a, 2007b).

³See Crespo Cuaresma and Lutz (2007) for evidence on the importance of the demographic dimension for explaining differences in income and income growth across countries.

estimation requirement that the cross-section dimension is dominated by the time dimension.

Figures 1 to 8 present the histograms of the different distance measures for the sample at hand. Distance plots based on the shares of age-structured human capital for the four country sub-groups are presented in Figures 1 and 2. Similarly, Figures 3 and 4 depict distance plots based on the input share of human capital in production for each country. Further disaggregation is made for the male population (Figures 5 and 6) and for the female population (Figures 7 and 8) based on the proportion of age-structured human capital for each sex in the total population.

Table 1: List of countries.

Asia	Africa	Europe	LatAmericaoffshore
Bahrain	Benin	Austria	Argentina
Bangladesh	Burki Faso	Belgium	Australia
Cambodia	Cameroon	Bulgaria	Bolivia
China	CentAfrRepub	Denmark	Brazil
Hong Kong	Chad	Finland	Canada
India	Cte d'Ivoire	France	Chile
Indonesia	Egypt	Germany	Colombia
Iran	Gabon	Greece	Costa Rica
Japan	Ghana	Hungary	Cuba
Jordan	Guinea	Ireland	Dom.Republic
Malaysia	Kenya	Italy	Ecuador
Nepal	Madagascar	Netherlands	El Salvador
Pakistan	Malawi	Norway	Guatemala
Philippines	Mali	Poland	Honduras
Singapore	Mauritius	Portugal	Mexico
S.Korea	Morocco	Romania	New Zealand
Sri Lanka	Mozambique	Spain	Panama
Syria	Namibia	Sweden	Paraguay
Thailand	Niger	Switzerland	Peru
Turkey	Nigeria	UK	USA
Vietnam	South Africa		Uruguay
	Togo		
	Uganda		
	Zambia		
	Zimbabwe		
N = 21	N = 25	N = 20	N = 21

4 Empirical Results

This section discusses the estimation results of the SVAR model outlined above for the different groups of countries and two alternative human capital distance measures.

The coefficient estimates for α and σ^2 based on the two measures of distance can be found in Tables 2 and 3. Note that $\hat{\alpha}$ values in the two tables are the average estimates over countries for a given region. The significance of the coefficients can be gauged by calculating the corresponding pooled t-ratio. Table 2 reports the parameter estimates of the SVAR using the demographic-economic distance matrix calculated by taking the average of the age shares over four decades for each country enlisted in each region. The significance of the averaged estimate of α is indicative for the presence of autocorrelation for the region under investigation. From Table 2 it is evident that the $\hat{\alpha}$ for each region is not particularly large, however, Europe and Latin America and Offshore countries exhibit significant estimates of α . The same conclusion holds for Table 3 where the distance measure is based on appropriation of human capital in the production of one unit of output. The averaged conditional variances ($\hat{\sigma}^2$) for each region described by

idiosyncratic components (σ_i^2) are also presented. While the results for α appear very consistent across estimations with different distance measures, some relevant differences appear in the point estimates of the average variance. This gives us a first indication concerning the fact that the two measures give rise to potentially different covariance dependence structures in the error term, an issue which will be assessed directly by the estimates of the γ function.

Table 2: Parameter estimates $\hat{\alpha}$ and $\hat{\sigma}^2$ with age-structured human capital shares.

Regions	$\hat{\alpha}$		$\hat{\sigma}^2$		Obs.
	Coef.	Std-Dev.	Coef.	Std-Dev.	
Africa	0.0281	0.1418	0.0052	0.0018	1716
Asia	0.1810	0.1361	0.0063	0.0023	1452
Europe	0.2126	0.1268	0.0008	0.0003	924
Latin America & offshore	0.2244	0.1404	0.0016	0.0005	1144

Table 3: Parameter estimates $\hat{\alpha}$ and $\hat{\sigma}^2$ with input share of human capital in production.

Regions	$\hat{\alpha}$		$\hat{\sigma}^2$		Obs.
	Coef.	Std-Dev.	Coef.	Std-Dev.	
Africa	0.0272	0.1414	0.0039	0.0020	1716
Asia	0.1852	0.1373	0.0037	0.0020	1452
Europe	0.2158	0.1288	0.0008	0.0003	924
Latin America & offshore	0.2305	0.1400	0.0005	0.0005	1144

Figures 9 to 24 present the plots of the estimates of the f and γ functions with respect to the respective distance metrics in different subsamples. In each case the solid line is the point estimate of f or γ plotted over the range of distances in our sample. The crosses correspond to a 95% bootstrap confidence interval around the estimate.

The results for Europe (Figures 9 to 12) present evidence of significant spatial effects depending on the human capital distance, although the nature of the channel identified differs across metrics. Using the age-structured human capital distance (Figure 10), we notice that the point estimates for f appear positive and significant for relatively short distances. A significant non-linear pattern is also observed, with the effect levelling out at an increasing rate as distance increases. We therefore show evidence of complementarity in the growth process which is regulated by the similarity in the demographic distribution of the human capital stock and the importance of human capital in the production process. For large distances, the effect is still positive but highly non-linear and unprecisely estimated. No significant spatial effects appear in the covariance structure using this measure of distance, with a $\hat{\gamma}$ function which is significant only at zero distance. It is noticeable that, when disaggregating data by gender, this effect is only captured by the distance based on female population.

The situation is more revealing as we look at the γ function. The estimated shape of the γ function as plotted in Figure 9 (right side) shows the expected pattern: the covariances of the residuals between countries are monotonically decreasing with distance. The effect is not present in a significant manner if the demographic metric is used, as shown in Figure 10. It should be

noticed that the estimates presented in the figures are those of γ divided by the country variance estimates. This normalization would render an estimate of the spatial correlation if the shock variances were identical across countries. Notice that the magnitude of the estimates of γ is quite large for the first distance metric and small but positive and constant for the latter. Using the former, there is strong evidence that shocks in our VAR model are spatially correlated as a function of distance in the specification which uses the elasticity measure to define the space metric.

Figures 13 and 14 present significant spatial persistence for the defined two measures of economic distance in the Asian group. For both distance measures, the f functions are significant. For elasticity-based measures, the f function is positive on the average, most importantly at the higher distances, assuming a peak in the middle. With the human capital distribution based measure, the f function is negative and significant on average for most distances. Being labor-dominant economies, the Asian countries' production function can assume striking similarity based on the amount of input used for production. Thus, the elasticity-based distance measure can reveal more about the interdependence nature of Asian economies, although the distribution of human capital across age and gender (Figures 15 and 16) is a good indicator of demographic similarity. Putting the results together, we observe a weak form of spatial autocorrelations based on the proposed distance metrics. Importantly, a still highly non-linear pattern of the f function is observed for all distance measures across gender and aggregate population, which reinforces the evidence found in the European case.

Latin America and offshore countries also exhibit spatial persistence due to the defined distance measures although the degree of persistence appears to be low in magnitude (Figures 21 and 22). The f functions in Figures 21 and 22 depict different patterns and appear thus to be sensitive to the distance metrics used. The f function responds non-linearly to the distance variation due to demography-based human capital share (Figure 22) such that significant spatial autocorrelation can be discerned at most distances. With respect to the distinction of the male and female population's contribution to spatial volatility in these regions (Figures 23 and 24), we find no significant differences in both f and γ functions.

For African countries (Figures 17 and 18), however, no significant spatial persistence patterns are discerned. However, as expected the γ functions in Figures 17 and 18 indicate that the residual variances from the regression decline with distances. Similar conclusions follow for male and female populations in this region (Figures 19 and 20).

Summing up, for most country groups the growth processes are observed to be complementary and the corresponding stochastic error terms in these countries can also be explained as functions of economic distances.

5 Discussion and Conclusions

This paper is the first full econometric study aimed at the quantification of cross-country growth spillovers based on human capital similarity measures, using the recently developed IIASA-VID human capital database. We make use of the innovative nature of the educational attainment data described by age and sex and estimate a multivariate semi-parametric spatial time series model where the coefficients of the vector autoregressive structure and of the covariances of the error terms were modeled as a function of the economic distance between countries. At a broader level, we were motivated by the fact that unveiling the determinants of the interaction patterns of output growth may give foot to developing and testing theories of endogenous growth. Specifically, this study concerned the macroeconomic effects of the age-structured human capital

distribution in the following geographical groups: Asia, Africa, Europe and Latin America and Offshore countries.

The overall finding is that there is a significant degree of cross-country growth volatility which can be attributed to shock correlation based on human capital similarity. In this respect, national growth processes are complementary to each other with respect to the proposed distance metric (based on the proportion of age-structured human capital growth or elasticity of human capital in the production). This result should therefore be taken into account when evaluating the potential advantages of cross-national cooperation in demographic and education policy management.

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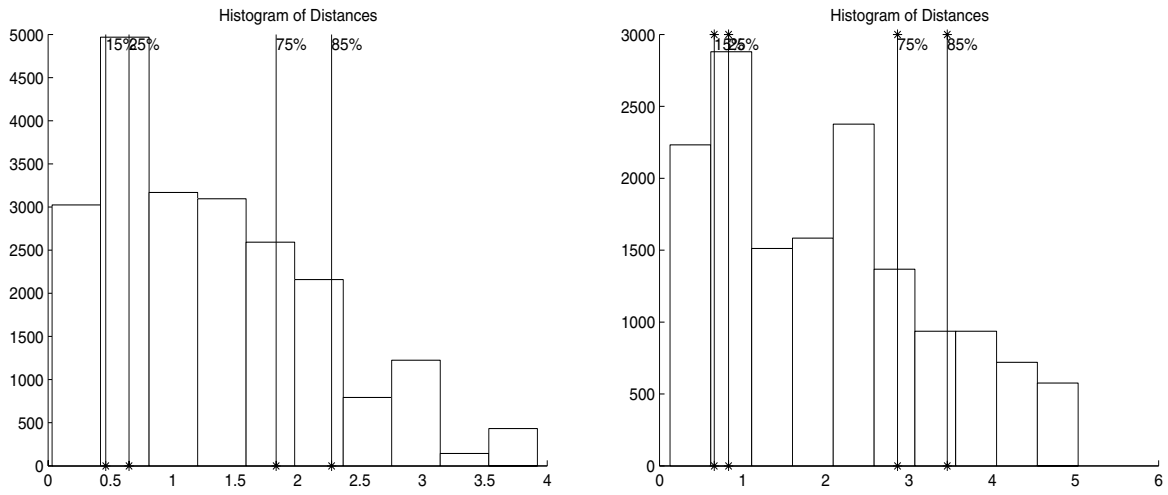


Figure 1: Histogram of distances based on aggregate population on age-structured human capital share: Africa (left), Asia (right).

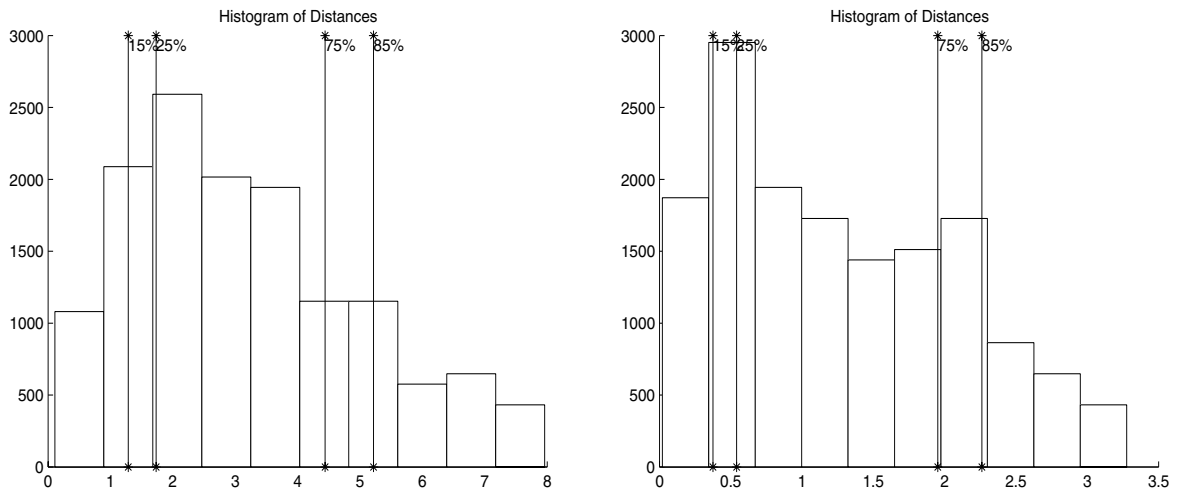


Figure 2: Histogram of distances based on aggregate population on age-structured human capital share: Europe (left), Latin America and Offshore (right).

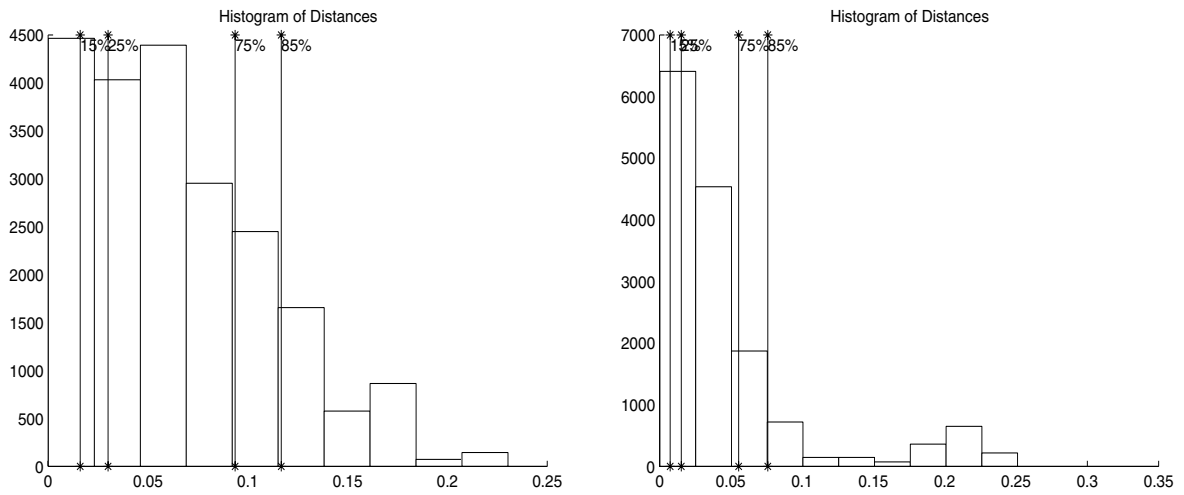


Figure 3: Histogram of distances based on aggregate population on elasticity of capital share: Africa (left), Asia (right).

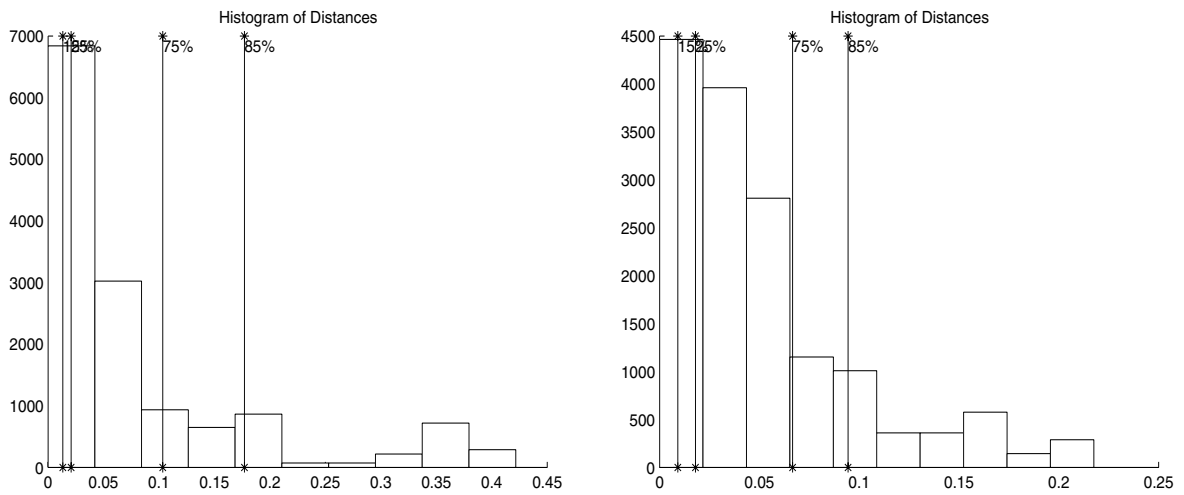


Figure 4: Histogram of distances based on aggregate population on elasticity of human capital share: Europe (left), Latin America and Offshore (right).

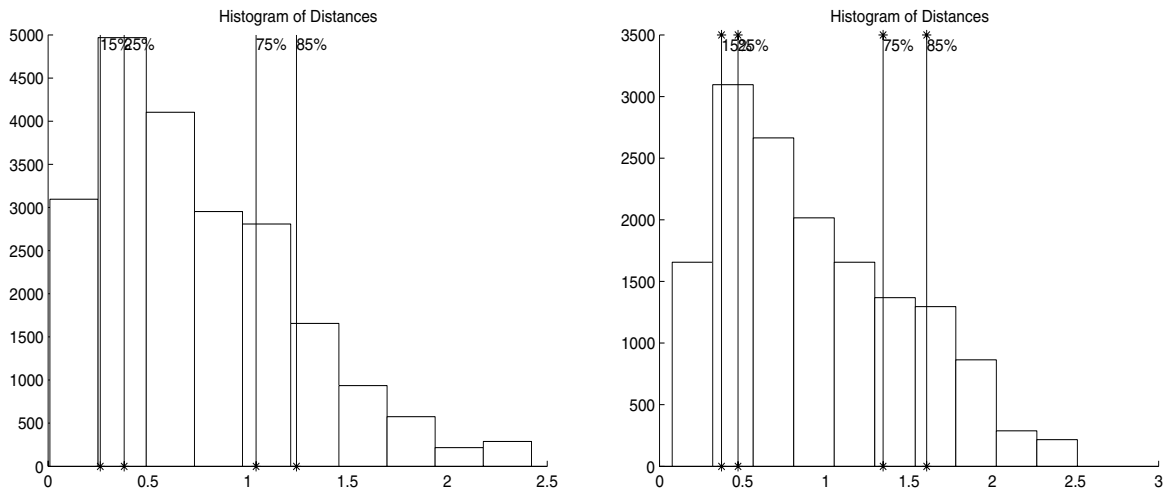


Figure 5: Histogram of distances based on male population on age-structured human capital share: Africa (left), Asia (right).

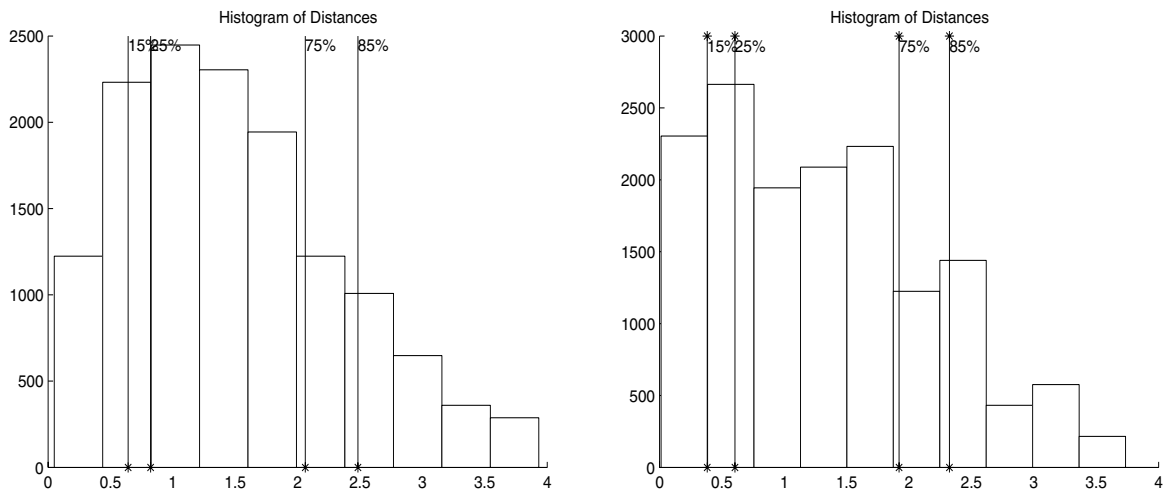


Figure 6: Histogram of distances based on male population on age-structured human capital share: Europe (left), Latin America and Offshore (right).

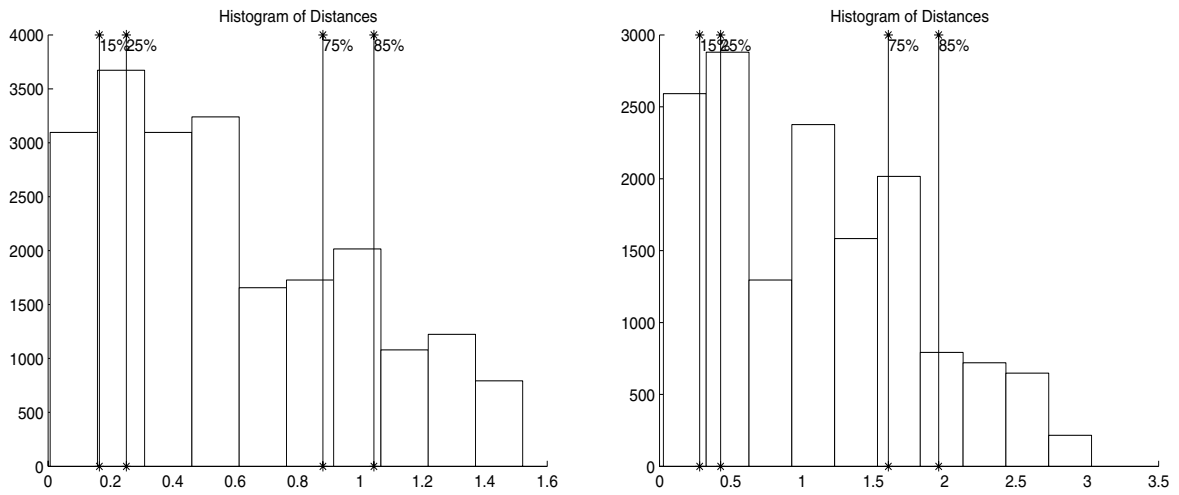


Figure 7: Histogram of distances based on female population on age-structured human capital share: Africa (left), Asia (right).

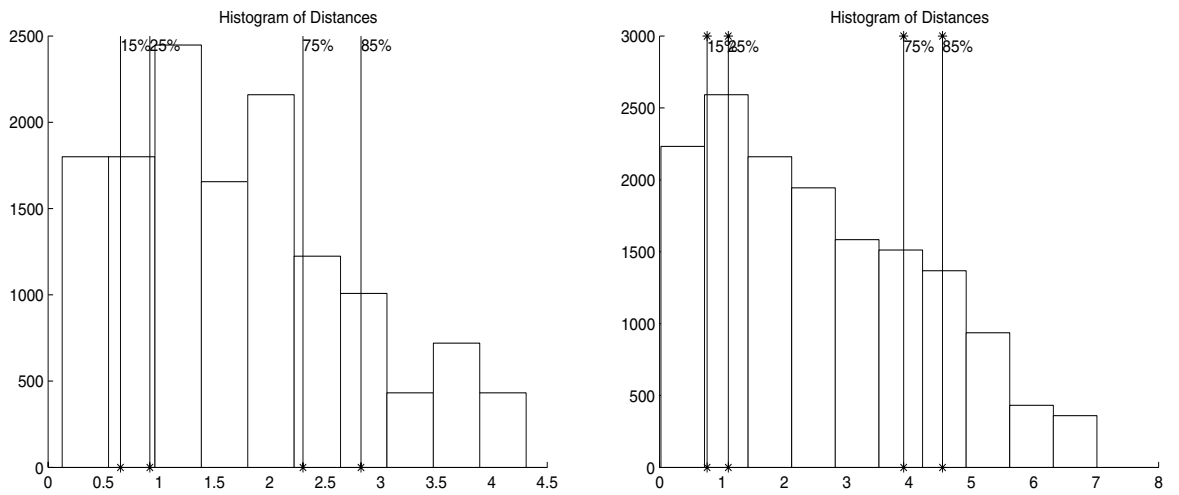


Figure 8: Histogram of distances based on female population on age-structured human capital share: Europe (left), Latin America and Offshore (right).

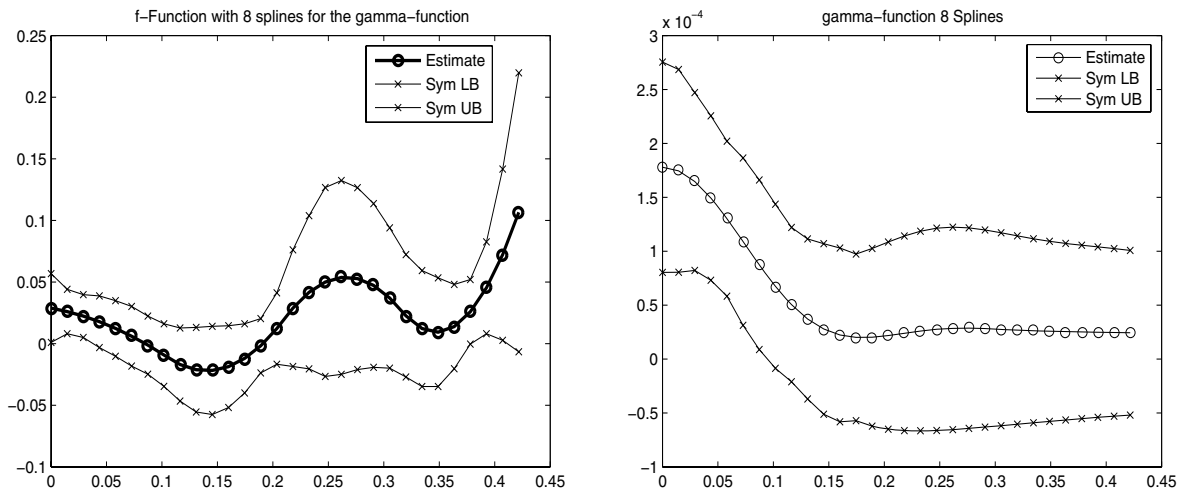


Figure 9: Conditional mean (\hat{f} [left]) and covariance ($\hat{\gamma}$ [right]) functions based on elasticity measure: Total population for Europe.

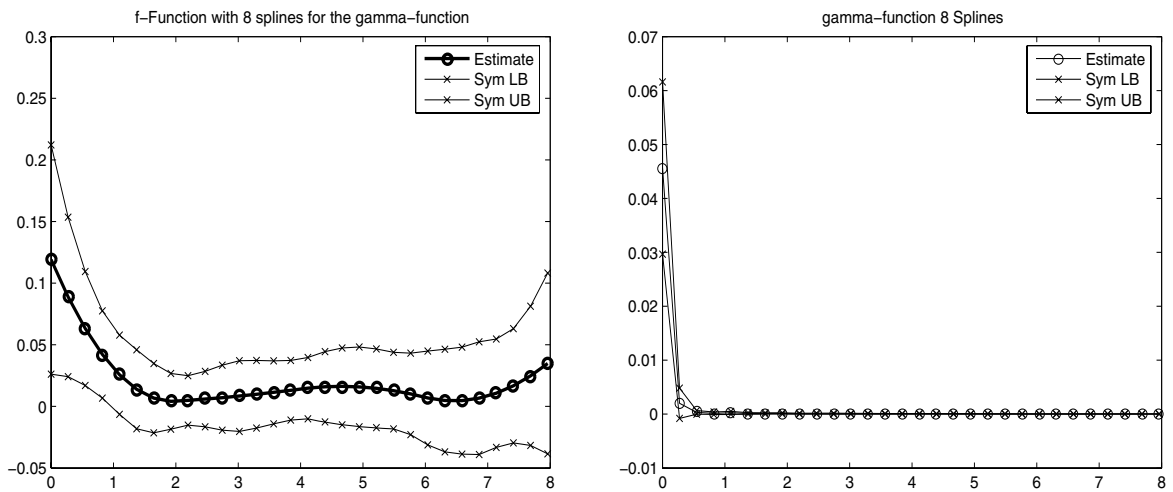


Figure 10: Conditional mean (\hat{f} [left]) and covariance ($\hat{\gamma}$ [right]) functions based on demography-based human capital share: Total population for Europe.

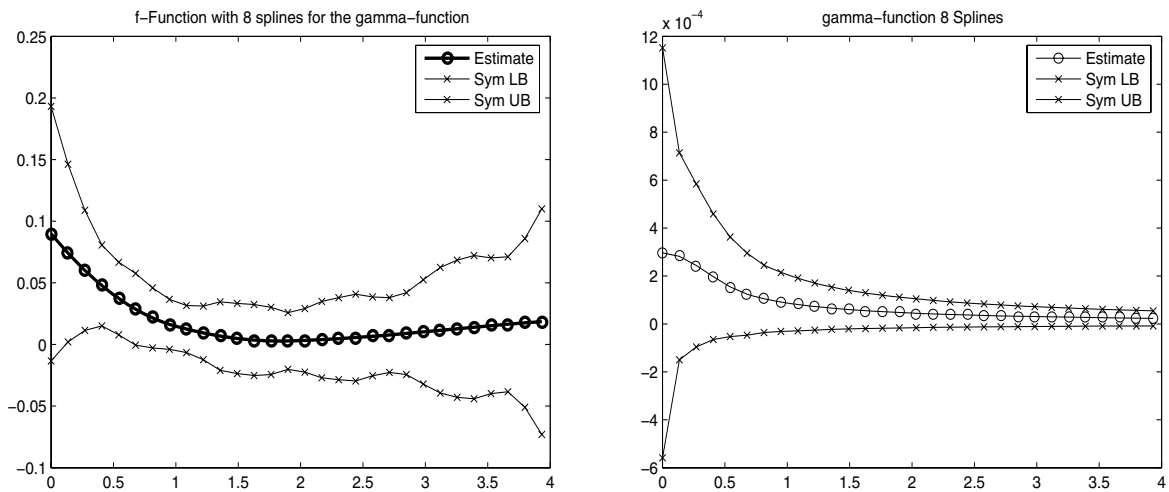


Figure 11: Conditional mean (\hat{f} [left]) and covariance ($\hat{\gamma}$ [right]) functions based on demography-based human capital share: Male population for Europe.

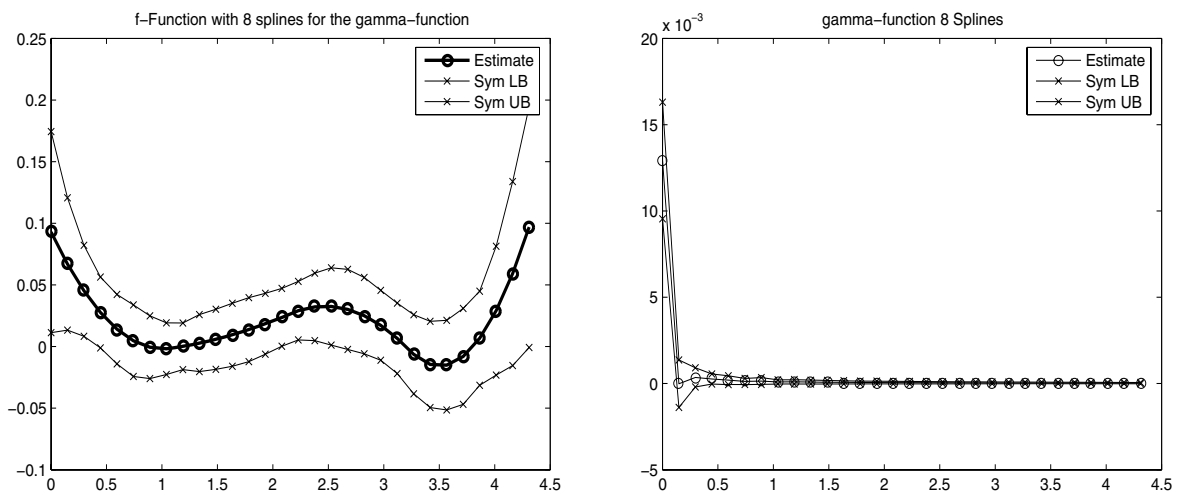


Figure 12: Conditional mean (\hat{f} [left]) and covariance ($\hat{\gamma}$ [right]) functions based on demography-based human capital share: Female population for Europe.

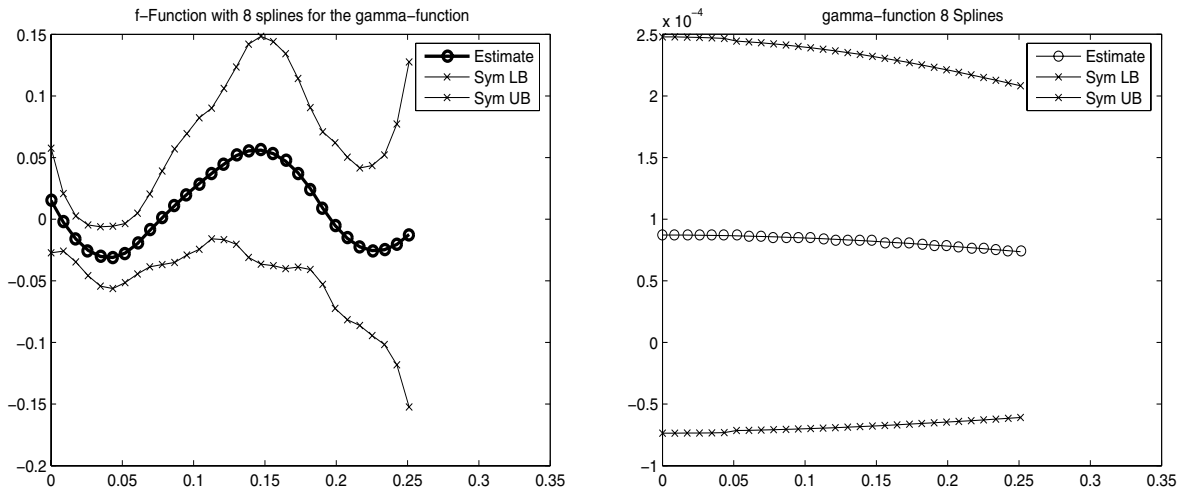


Figure 13: Conditional mean (\hat{f} [left]) and covariance ($\hat{\gamma}$ [right]) functions based on elasticity measure: Total population for Asia.

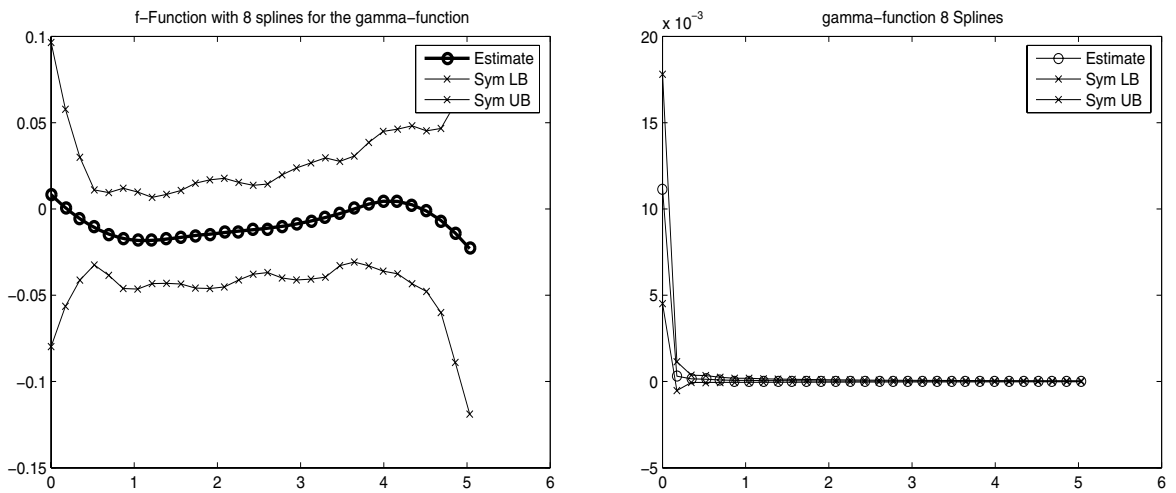


Figure 14: Conditional mean (\hat{f} [left]) and covariance ($\hat{\gamma}$ [right]) functions based on demography-based human capital share: Total population for Asia.

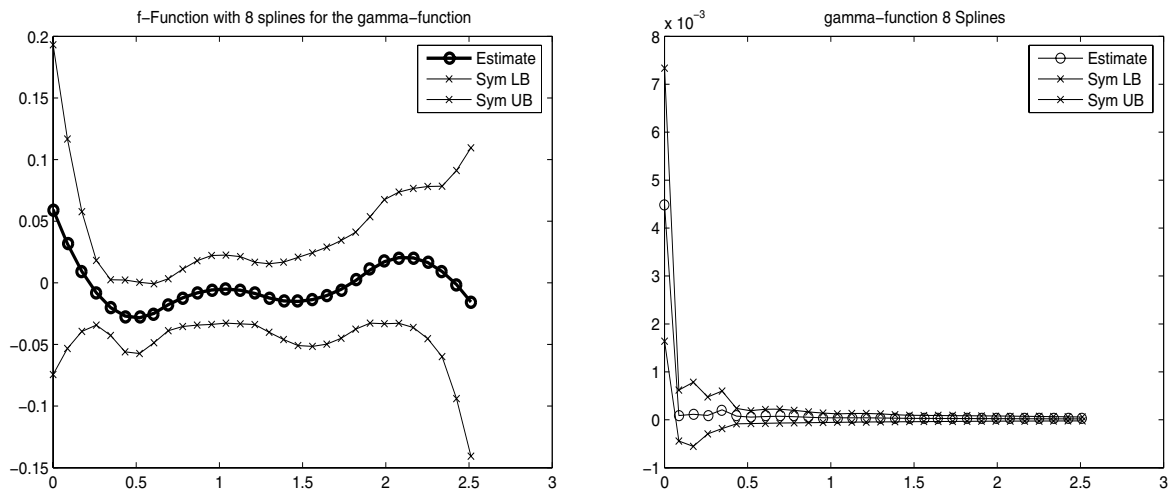


Figure 15: Conditional mean (\hat{f} [left]) and covariance ($\hat{\gamma}$ [right]) functions based on demography-based human capital share: Male population for Asia.

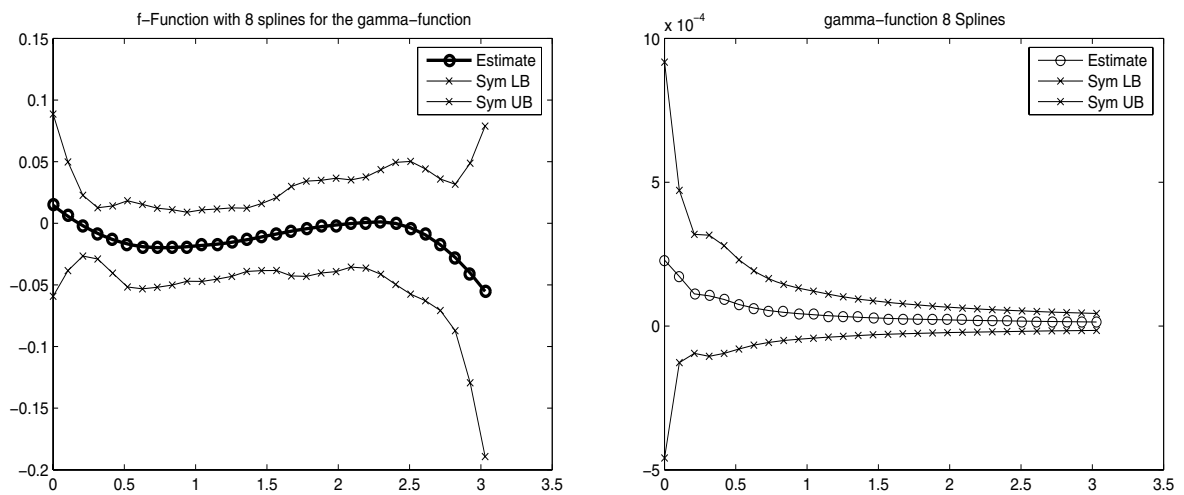


Figure 16: Conditional mean (\hat{f} [left]) and covariance ($\hat{\gamma}$ [right]) functions based on demography-based human capital share: Female population for Asia.

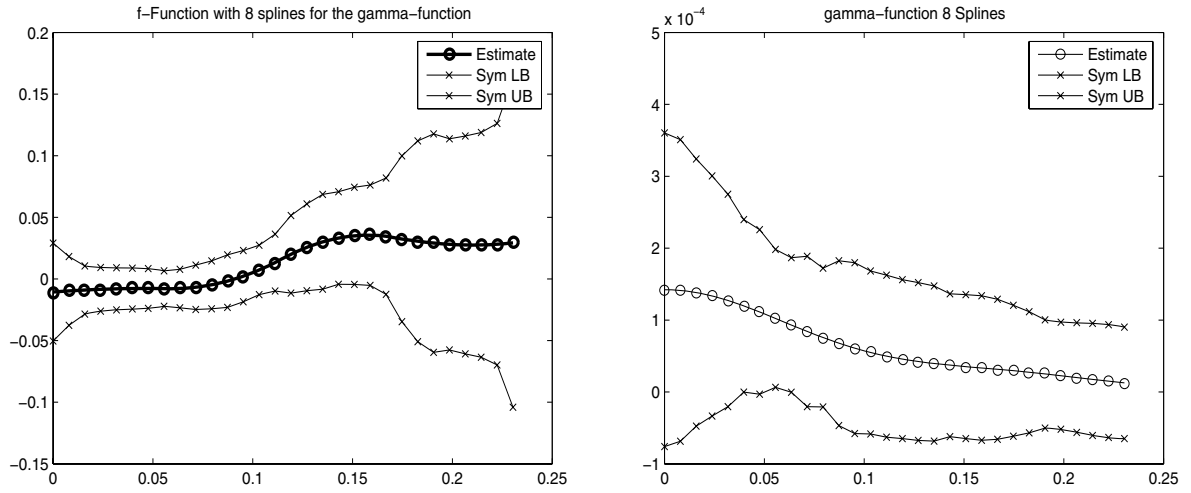


Figure 17: Conditional mean (\hat{f} [left]) and covariance ($\hat{\gamma}$ [right]) functions based on elasticity measure: Total population for Africa.

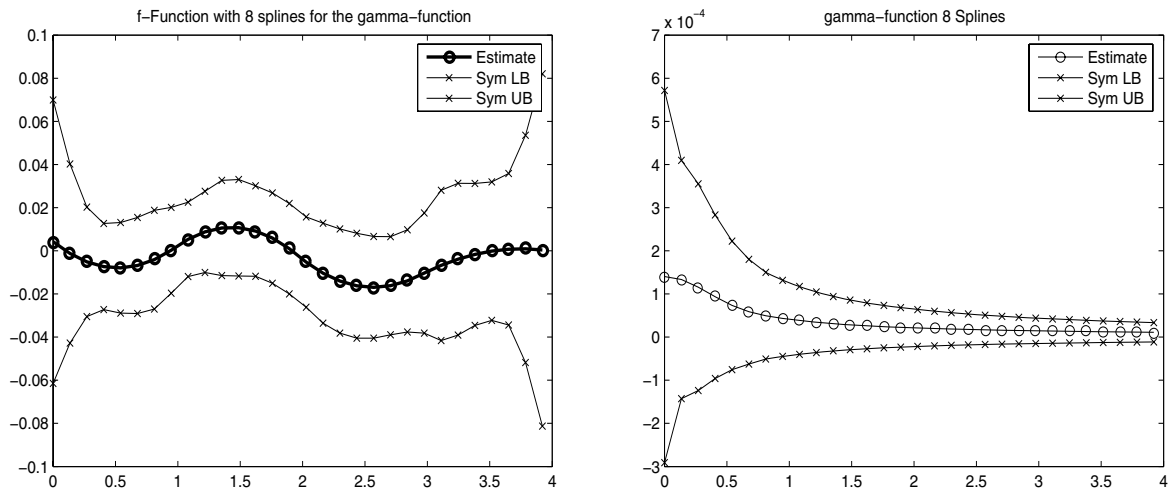


Figure 18: Conditional mean (\hat{f} [left]) and covariance ($\hat{\gamma}$ [right]) functions based on demography-based human capital share: Total population for Africa.

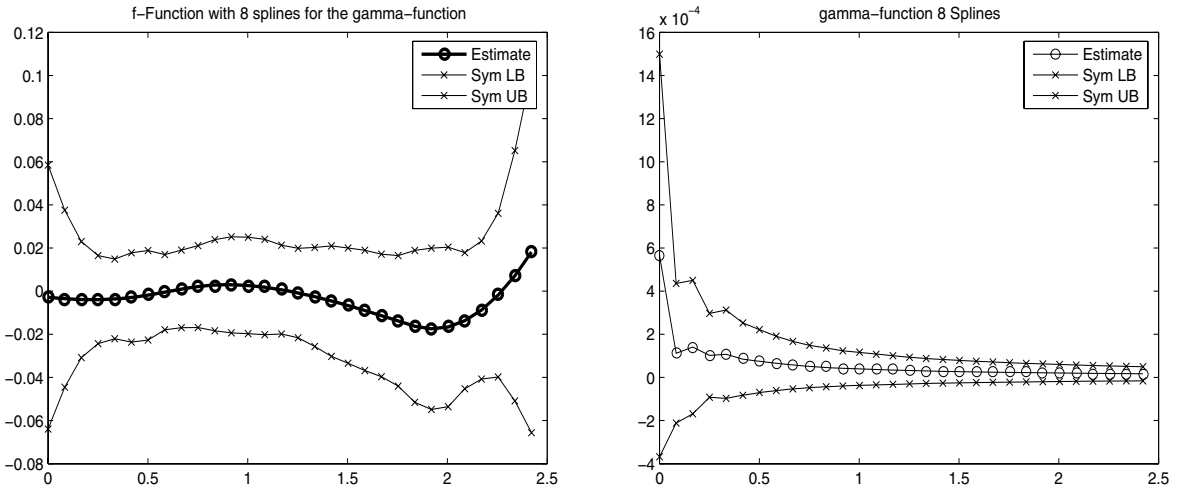


Figure 19: Conditional mean (\hat{f} [left]) and covariance ($\hat{\gamma}$ [right]) functions based on demography-based human capital share: Male population for Africa.

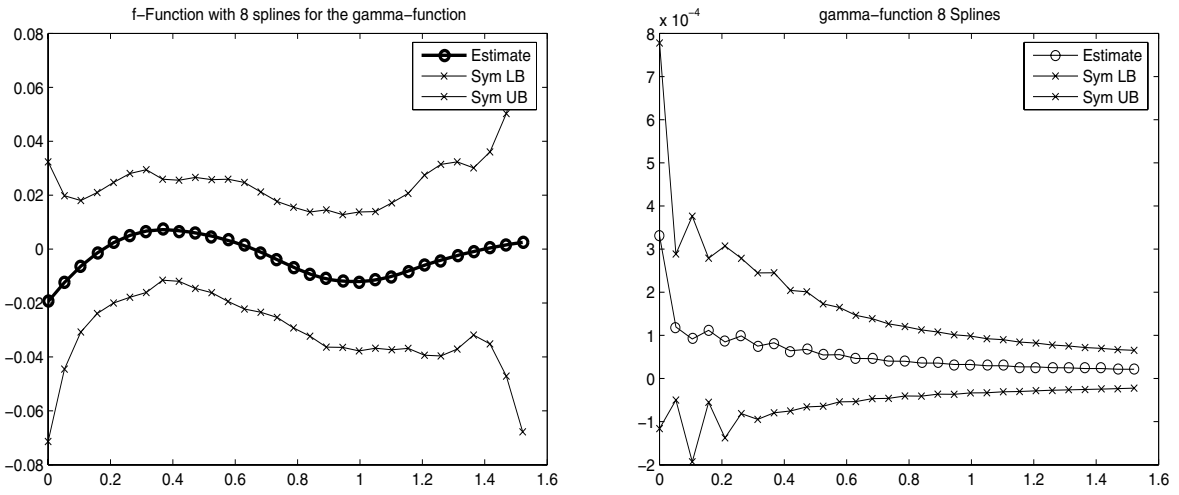


Figure 20: Conditional mean (\hat{f} [left]) and covariance ($\hat{\gamma}$ [right]) functions based on demography-based human capital share: Female population for Africa.

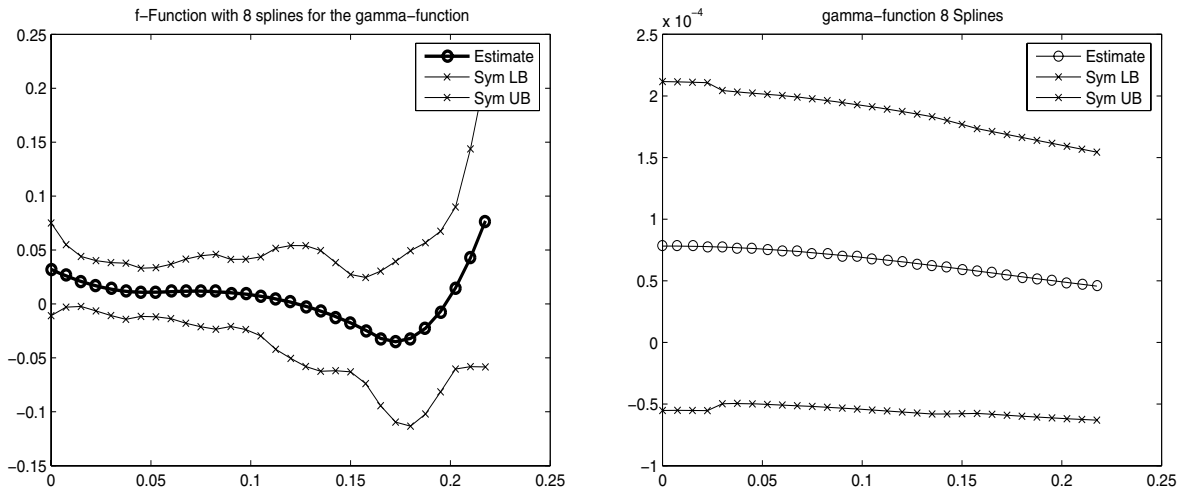


Figure 21: Conditional mean (\hat{f} [left]) and covariance ($\hat{\gamma}$ [right]) functions based on elasticity measure: Total population for Latin America and Offshore.

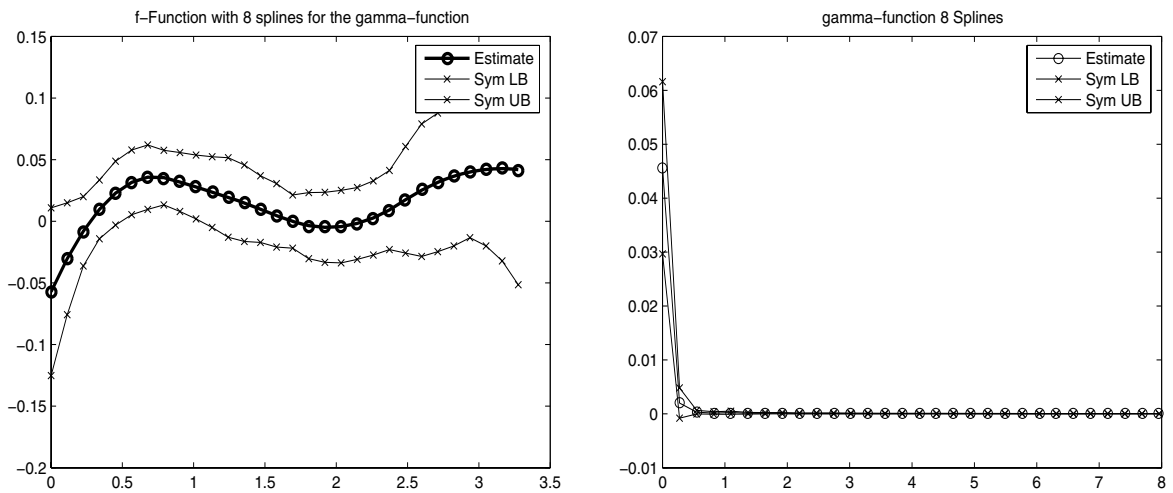


Figure 22: Conditional mean (\hat{f} [left]) and covariance ($\hat{\gamma}$ [right]) functions based on demography-based human capital share: Total population for Latin America and Offshore.

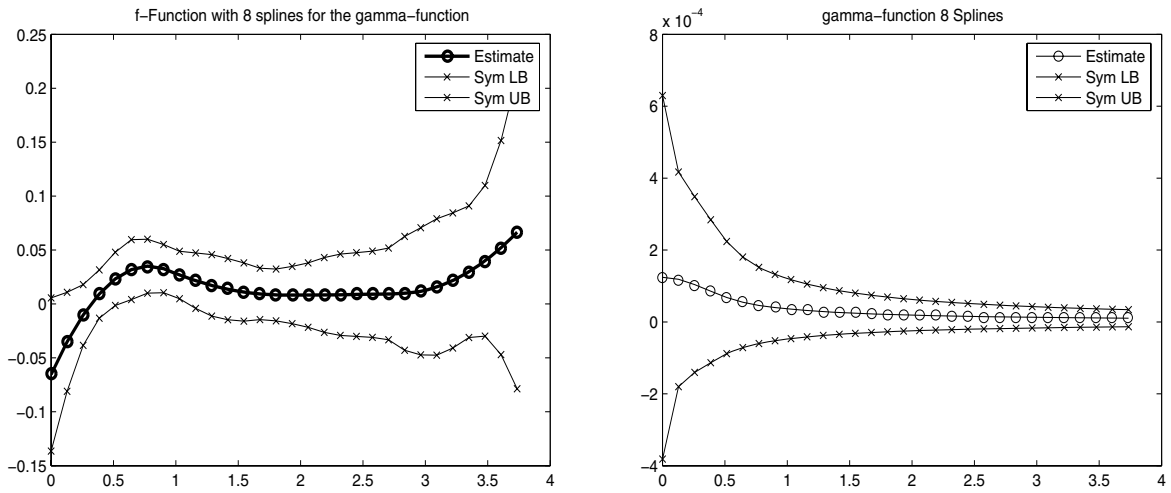


Figure 23: Conditional mean (\hat{f} [left]) and covariance ($\hat{\gamma}$ [right]) functions based on demography-based human capital share: Male population for Latin America and Offshore.

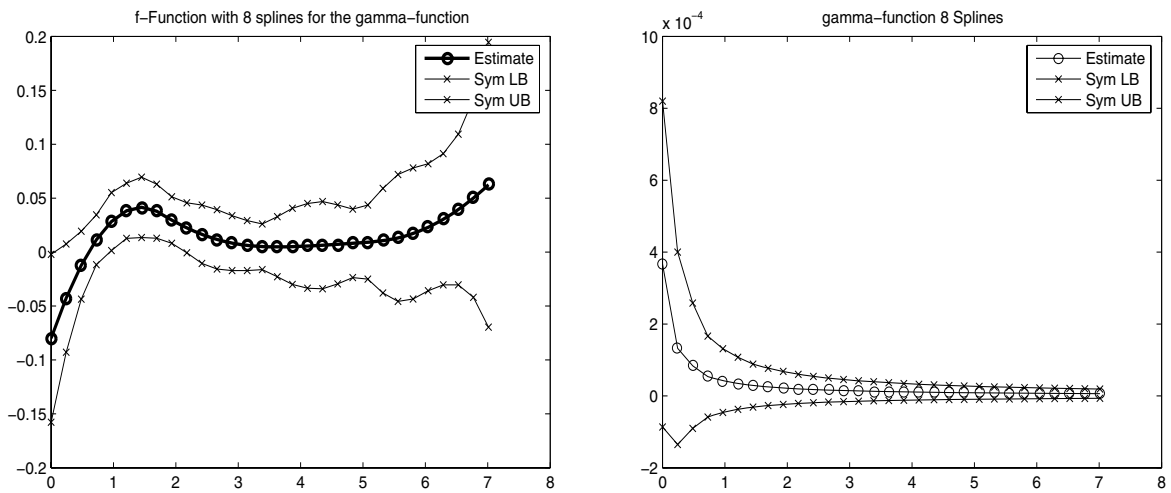


Figure 24: Conditional mean (\hat{f} [left]) and covariance ($\hat{\gamma}$ [right]) functions based on demography-based human capital share: Female population for Latin America and Offshore.