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Non-linearity in the Inflation-Growth Relationship in Developing Economies: Evidence from a Semiparametric Panel Model

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Non-linearity in the Inflation-Growth Relationship in Developing Economies: Evidence from a Semiparametric Panel Model*

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Abstract

Using data on developing economies, we estimate a flexible semiparametric panel data model that incorporates potentially nonlinear effects of inflation on economic growth. We find that inflation is associated with significantly lower growth only after it reaches about 12 percent, which is notably lower than the comparable estimate obtained from a threshold model. Our results also suggest that models with restrictive functional form assumptions tend to underestimate marginal effects of inflation on economic growth. We also document significant variation in the effect of inflation on growth across countries and over time.

Keywords: Inflation, economic growth, semiparametric panel data model, series estimation, bootstrap.

JEL Classification: O40, C23.

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1 Introduction

An extensive empirical literature examines the relationship between inflation and economic growth. The findings are wide-ranging and seem to depend on the methodology and sample under consideration. Earlier studies, such as Bruno and Easterly (1998) and Ghosh and Phillips (1998), either rely on descriptive techniques or do not account for country fixed effects in regression analysis. Khan and Senhadji (2001), Bick (2010), and Kremer et al. (2012) assume that nonlinearity is described by a piecewise linear structure and estimate threshold models with country fixed effects. The common finding from these studies is that inflation has a negative and significant effect on economic growth above a certain threshold, but the threshold estimates are sensitive to modeling assumptions.

In this paper we focus on the nonlinear aspects of the inflation-growth relationship in developing economies.[1] In particular, we consider a semi-parametric panel data model with country fixed effects and use the estimation techniques proposed by Baltagi and Li (2002). In addition, we use an iterative fixed design wild-bootstrap procedure for bias correction and inference. This flexible modeling framework allows us to estimate effects of inflation on economic growth at different rates of inflation without imposing restrictive functional form assumptions.

Our findings based on data from 92 countries from 1975-2004 can be summarized as follows. First, similar to the aforementioned studies that use threshold models, we also find that inflation becomes a significant detriment to growth only after it reaches a certain level. However, our estimate of the inflation rate that is associated with a reduction in economic growth is well below the estimate from the parametric threshold model. Second, the partial effect of inflation exhibits a highly non-linear pattern. In particular, as one may expect, we find that the marginal effect of a percentage point increase in inflation on growth declines considerably as inflation reaches relatively high levels. Third, our estimates suggest that the effect of inflation on growth over the range where it is statistically significant is notably larger than those obtained from linear or threshold models. Fourth, we find considerable cross-sectional and time-series variation in the partial effect of inflation on growth, which emphasizes importance of heterogeneity in the growth dynamics and historical inflation experience across countries.

The rest of the paper is organized as follows. We present the semi-parametric panel data model and discuss related methodological issues in Section 2. Section 3 introduces the data and presents the empirical results. Finally, section 4 concludes.

[1]Several papers utilize nonparametric methods to model nonlinearities in empirical growth regressions. In particular, Liu and Stengos (1999) proposed an additive semi-parametric specification, which stimulated a large body of research, e.g. Durlauf et al. (2001), Mamuneas et al. (2006) and Kalaitzidakis et al. (2001).

2 Methodology

The semiparametric panel data model of interest is given by

$$y_{it} = \alpha_i + \gamma' x_{it} + g(z_{it}) + u_{it}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T, \tag{1}$$

where α_i's represent unit fixed effects, x_{it} is a d-dimensional vector of possibly endogenous regressors, $g(\cdot)$ is a smooth function, z_{it} is an r-dimensional vector of exogenous regressors, and u_{it} are zero mean $i.i.d.$ innovations with variance σ_u^2. Thus, the model incorporates heterogeneity through individual fixed effects and allows analysis of the nonlinear relationship without imposing any specific functional form. Moreover, other relevant explanatory variables are accounted for in a standard linear fashion.

To perform estimation, we first difference the data to eliminate the unobserved heterogeneity, α_i. This yields,

$$Y_{it} = \gamma' X_{it} + G(z_{it}, z_{it-1}) + U_{it},$$

where $Y_{it} = y_{it} - y_{it-1}$, and the right hand side variables are defined similarly. A further simplification can be obtained by writing the model in the following form

$$Y = X\gamma + G + U, \tag{2}$$

where Y is $NT \times 1$ with typical element Y_{it}, and X, G and U are constructed similarly.

Baltagi and Li (2002) propose estimating the model in Equation (2) with the series method. They use K basis functions, say $p^K(z) = (p_1(z), \ldots, p_K(z))$, to approximate the unknown function $g(z)$. Therefore, $p^K(z_{it}, z_{it-1}) \equiv (p^K(z_{it}) - p^K(z_{it-1}))$ approximates $G(z_{it}, z_{it-1}) \equiv g(z_{it}) - g(z_{it-1})$. Let $p_{it}^K = p^K(z_{it}, z_{it-1})$ and $P = (p_{11}^K, p_{12}^K, \ldots, p_{1T}^K, \ldots, p_{N1}^K, \ldots, p_{NT}^K)'$ and define $M = P(P'P)^{-1}P'$.[2] Pre-multiplying all variables in Equation (2) with M and subtracting from the original equation yields

$$Y - \widetilde{Y} = (X - \widetilde{X})\gamma + (G - \widetilde{G}) + (U - \widetilde{U}),$$

where $\widetilde{Y} = MY$, $\widetilde{X}$ and $\widetilde{G}$ are similarly defined. As shown by Baltagi and Li (2002), we can consistently estimate γ by running the least squares regression of $(Y - \widetilde{Y})$ on $(X - \widetilde{X})$ since $\tilde{G} - G$ is negligible under regularity conditions for estimating γ. This yields

$$\widehat{\gamma} = \left[(X - \widetilde{X})'(X - \widetilde{X}) \right]^{-1} (X - \widetilde{X})'(Y - \widetilde{Y}).$$

Then $g(z)$ can be estimated by $\widehat{g}(z) = p^K(z)'\widehat{\delta}$ where $\widehat{\delta} = (P'P)^{-1}P'(Y - X\widehat{\gamma})$.

[2] For series estimation, power series and Legendre polynomials are used as the basis functions.

In our dynamic panel application, the presence of initial income level on the right-hand side causes bias in the first stage estimates. Several methods have been proposed in the literature to deal with similar bias arising in dynamic panel models. Kiviet (1995) corrects the least squares dummy variable (LSDV) estimator using an analytical approximation formula while Areallano and Bover (1995) and Blundell and Bond (1998) develop a system GMM method that uses suitable lagged levels and lagged first differences of the regressors as instruments. More recently, Everaert and Pozzi (2007) proposed an iterative bootstrap procedure for dynamic panel data models. We find that GMM confidence intervals for the parameters of the linear portion of the model are too wide such that no control, including the initial income level, is significant. This is in contrast with the established findings in the empirical growth literature. Therefore, we implement an iterative bootstrap procedure to deal with the bias arising from endogeneity of the initial income and use a fixed-design wild bootstrap procedure.[3] This approach has the additional benefit of improving inference on the nonparametric component of the model as asymptotic normal approximations for the nonparametric function may perform poorly in finite samples. In addition, inference results from the fixed-design wild bootstrap procedure are also robust to presence of cross sectional and temporal clustering in the innovations.

Implementation of the semi-parametric estimation procedure requires determination of the number of basis functions, K, which can be considered as an analog to the smoothing parameter (bandwidth) in kernel based nonparametric analysis. Thus, picking a small number of approximating functions may generate an over-smoothed (high bias, low variance) estimator while selecting too many approximating functions may produce an under-smoothed (low bias, high variance) estimator. Therefore, we estimate the number of basis functions by minimizing a well-defined objective function. In particular, we employ generalized cross-validation (GCV) and Mallow's criterion:

$$\widehat{K}_{GCV} = \arg\min_{K} \frac{(NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{it}-\widehat{g}(z_{it}))^2}{(1-(\frac{K}{NT}))^2},$$

$$\widehat{K}_{C_L} = \arg\min_{K} \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{it}-\widehat{g}(z_{it}))^2 + 2\sigma^2\frac{K}{NT},$$

where σ^2 is the variance of u_{it}. Following Su and Ullah (2006), we conduct this search in the $\left[\lceil nT\rceil^{1/4}, \lceil nT\rceil^{1/3}\right]$ range, where $\lceil x\rceil$ denotes the integer part of x.

[3] See Appendix B for a detailed description of the bootstrap procedure that we employ.

3 Data and Empirical Results

Our empirical application of the semi-parametric panel data model to the inflation-growth relationship in developing economies is based on a subset of the data set used in Kremer et al. (2012). They consider 124 industrialized and developing countries through the period 1950 to 2004. Since our methods require a balanced panel, we eliminate the countries that do not have data before 1975 and end up with a balanced panel of 92 developing countries from 1975 to 2004.[4]

We estimate the following semiparametric regression:

$$dgdp_{it} = \alpha_i + \gamma' x_{it} + g(\widetilde{\pi}_{it}) + u_{it},$$

where $dgdp_{it}$ is the growth rate of per capita GDP and the control variables, x_{it}, include population growth (*dpop*), investment as a share of GDP (*igdp*), the natural logarithm of income per capita of the previous period (*initial*), change in terms of trade (*dtot*), standard deviation of terms of trade (*sdtot*), the natural logarithm of the share of exports plus imports in the GDP as a measure of openness (*open*), and standard deviation of openness (*sdopen*).[5] We allow all right hand side variables other than inflation to be endogenous as in Kremer et al. (2012), so our results do not necessarily imply a causal effect from inflation to growth.[6] Following Khan and Senhadji (2001), we apply a semi-log transformation to inflation:

$$\widetilde{\pi}_{it} = \begin{cases} \pi_{it} - 1, & \text{if } \pi_{it} \leq 1\% \\ \ln(\pi_{it}), & \text{if } \pi_{it} > 1\% \end{cases}$$

where π_{it} denotes the actual inflation rate for country i at time t. This transformation, which is commonly used in the empirical literature on inflation-growth relationship, adjusts inflation data to minimize the effects of cross sectional heteroskedasticity while preserving continuity. The partial effect of inflation on growth, say $\beta(\widetilde{\pi})$, is simply obtained as the derivative of $g(\widetilde{\pi})$. In accordance with the empirical growth literature, we take 5-year averages of the variables.

We display the scatter plot of average inflation and average GDP growth in Figure 1 to get some insight into the unconditional relationship between growth and inflation. In general, we do not observe a particular pattern, especially at low levels of inflation, but as average inflation increases a weak negative relationship seems to appear.

[4] Appendix A contains a list of countries included in our analysis. Further details regarding the data set can be found in Kremer et al. (2012) and the data can be downloaded from http://www.public.asu.edu/ abick/.

[5] Recent empirical research finds little or no significant effect of years of education on economic growth (see Delgado et al. (forthcoming), Durlauf et al. (2008), and Liu and Stengos (1999)). Therefore, we do not include education, a proxy for human capital, among our control variables. This also allows for a direct comparison of our results with Kremer et al. (2012) who use the same set of controls.

[6] Using lagged inflation provides qualitatively similar results.

To implement the semiparametric panel model in practice we need to select the number of basis functions. Table 1 reports the number of basis functions and the corresponding loss from our selection metrics, generalized cross-validation and Mallow's criterion. We set $K = 8$ as this choice minimizes the loss according to both criteria.

Table 2 displays the coefficient estimates and bootstrap confidence intervals (at 90 percent level) for the control variables that enter the model linearly. Sign and magnitude of the estimates are broadly in line with the existing findings from the empirical growth literature. The marginal effect of initial per capita GDP on growth is negative and statistically significant. This finding is consistent with the conditional convergence hypothesis and suggests that countries with initially low income per capita tend to grow faster than countries with higher income per capita. Based on our bootstrap procedure, change in the terms of trade and share of investment in GDP affect growth positively and they are also statistically significant. Other controls are insignificant and the openness measure does not have the expected sign.

Our flexible semiparametric framework allows estimation of the unknown inflation function at all sample points, which stands in strong contrast with the conventional linear model as well as the threshold model that imposes a piecewise linear structure on the inflation function. Figure 2 presents the estimates of the partial effects of log-transformed inflation, $\beta(\widetilde{\pi})$, along with the general bootstrap confidence intervals at 90 percent confidence level. Two important points emerge from this figure. First, the point estimates are always negative, but the magnitude and statistical significance are largely dependent on the level of inflation. Second, the partial effect of inflation is significant only when log-transformed inflation is between 2.45 and 4.65, which corresponds to a range of about 12 to 105 percent for the underlying inflation rate. If we increase the confidence level to 95% (not shown on the figure), the lower bound of this range increases to 2.65 for the log-transformed inflation rate (about 15 percent for the underlying inflation rate) and the upper bound remains unchanged.

To assess economic significance of our estimates and compare to alternative approaches, we plot the corresponding partial effects with respect to inflation, say $\theta(\pi)$, in Figure 3. Since log-transformed inflation is used in the regression, the estimates presented in this figure are simply the partial effects with respect to the log-transformed inflation variable divided by the level of inflation, i.e. $\theta(\pi) = \beta(\widetilde{\pi})/\pi$. We present the results for inflation values ranging from 2 to 80 percent. Our estimates suggest that the partial effect of inflation attains its largest absolute value as inflation approaches double digits. In the 8-9 percent range, an additional 1 percent inflation is expected to be accompanied by about 0.1 percent slower growth rate in per capita income. Beyond 9 percent inflation, the estimated partial effect decreases monotonically in magnitude. Recall that the 90 percent bootstrap confidence intervals imply that inflation becomes a statistically significant determinant of growth when it reaches about 12 percent. At this level of inflation, the estimated partial effect is -0.097, which implies an economically meaningful difference in growth. The estimated partial effect is almost halved from this level when inflation reaches about 35 percent and converges to -0.02 percent when inflation is 80 percent. That is, as one may expect, at very high levels of inflation a small increase in the inflation rate has negligible effects on growth. These results highlight the importance of containing inflation at reasonably low rates.

Figure 3 also shows estimated partial effects from linear and threshold models. The threshold is estimated to be about 17 percent.[7] Once the threshold is breached, the partial effect of inflation on growth changes from about -0.005 to -0.02 and decreases in magnitude monotonically in accordance with the piecewise linear structure of the threshold model. The linear model and the threshold model provide almost identical estimates beyond the 17 percent threshold and both are well below in magnitude compared to our semiparametric estimates. The significant difference in the estimated magnitudes can be explained by the fact that the threshold model imposes the same partial effect at all levels of log-transformed inflation beyond the threshold and as a result the coefficient of inflation in the high inflation regime amounts to an average across moderately high and very high levels of inflation.

To sum up, the results suggest that under linear or piecewise linear functional form assumptions the partial effects of inflation on growth are much smaller in magnitude than those implied by our flexible semiparametric approach. Moreover, our estimates indicate that the threshold beyond which inflation becomes a statistically significant detriment to growth is also dependent on the functional form assumptions.

Parameter heterogeneity is considered to be an important issue in empirical growth literature and several authors document strong evidence for extensive heterogeneity (see e.g., Durlauf and Johnson (1995) and Masanjala and Papageorgiou (2004)). An attractive feature of our semiparametric approach is that we can shed light on the heterogeneity of the partial effects of inflation on growth across countries.[8] An effective way to summarize the results is to plot kernel density of the partial effect estimates. We first compute the median partial effect (across time) for each country in our sample and examine its distribution. Figure 4 shows the kernel density of the partial effect estimates across all countries in the sample using Gaussian kernel and optimal bandwidth, i.e. $h = 1.06\hat{\sigma}n^{-1/5}$. Almost all of the estimates fall in the negative region and the distribution has a large degree of dispersion. Moreover, the estimated density is trimodal with the first mode roughly equal to -0.4, the second one close to -1, and the third around -1.6. Thus, our results uncover an interesting aspect of the inflation-growth relationship: on average, the marginal effect of inflation is negative but considerable cross country variation is evident.

To gain further insight into the nature of the heterogeneity, we examine the cross sectional distribution of $\beta(\tilde{\pi})$ over each five year interval in the sample. The corresponding kernel

[7] We thank Alexander Bick for making the Matlab code for estimating the threshold model available on his website (http://www.public.asu.edu/ abick/).

[8] Henderson et al. (2013) and Henderson et al. (2012) find strong evidence for heterogeneous partial effects in growth regressions using nonparametric techniques.

density estimates are shown in Figure 5. The distribution during the first decade of the of the sample period (1975-1985) is roughly symmetric around -1. A bimodal density emerges in 1985-1990 according to which countries fall into one of two groups: the modal partial effect is close to -0.5 in the first group while it is close to -2 in the second. In the final period of the sample (2000-2004), the distribution clearly becomes trimodal with most countries having a partial effect estimate less than -1 and a small group distributed around -1.5. These results suggest that significant heterogeneity in the inflation-growth relationship emerged over time.

Finally, as a robustness check, we dropped insignificant controls from the linear portion of the model. The results for the nonparametric function and partial effects are shown in Figures 6 and 7. A comparison with Figures 2 and 3 reveals that results are highly qualitatively similar to the baseline case that includes all of the controls. The notable differences are that the restricted model implies slightly smaller partial effects, on average, and a lower value for the upper bound on the range of values for which inflation is statistically significant.

4 Concluding Remarks

We estimate a semiparametric empirical growth regression for developing economies in which inflation enters the equation in a potentially nonlinear way with an unknown functional form. We find that inflation becomes a significant detriment to growth only after it reaches about 12 percent, which is lower than the rate implied by a threshold model. Moreover, we also find that the relationship ceases to be statistically significant at very high levels of inflation. Our estimates for the partial effects indicate a larger impact of inflation on growth than the estimates obtained under parametric functional form assumptions. We also document considerable cross-sectional and time-series variation in the marginal effect of inflation on growth, which emphasizes the constantly evolving cross sectional growth dynamics within the developing world.

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Table 1: Basis Function Selection

K	Generalized CV	Mallow's Criterion
4	16.590	16.736
5	16.478	16.659
6	16.124	16.334
7	16.037	16.276
8	**15.927**	**16.202**

Notes: This table reports the number of basis functions (K) and the corresponding loss from two selection metrics: generalized cross-validation and Mallow's criterion. The range of K is determined with reference to Su and Ullah (2006).

Table 2: Bootstrap Confidence Intervals for Parametric Component of the Model

Variable	Point estimate	90% Confidence Interval
initial	-3.753	$[-5.124, -2.382]$
dpop	-0.334	$[-1.011, 0.344]$
dtot	0.102	$[0.052, 0.151]$
igdp	0.087	$[0.002, 0.172]$
open	-1.270	$[-2.68, 0.14]$
sdtot	0.043	$[-0.007, 0.093]$
sdopen	0.443	$[-0.081, 0.966]$

Notes: This table reports point estimates and bootstrap confidence intervals for the linear portion of the model.

Figure 1: Inflation and Growth

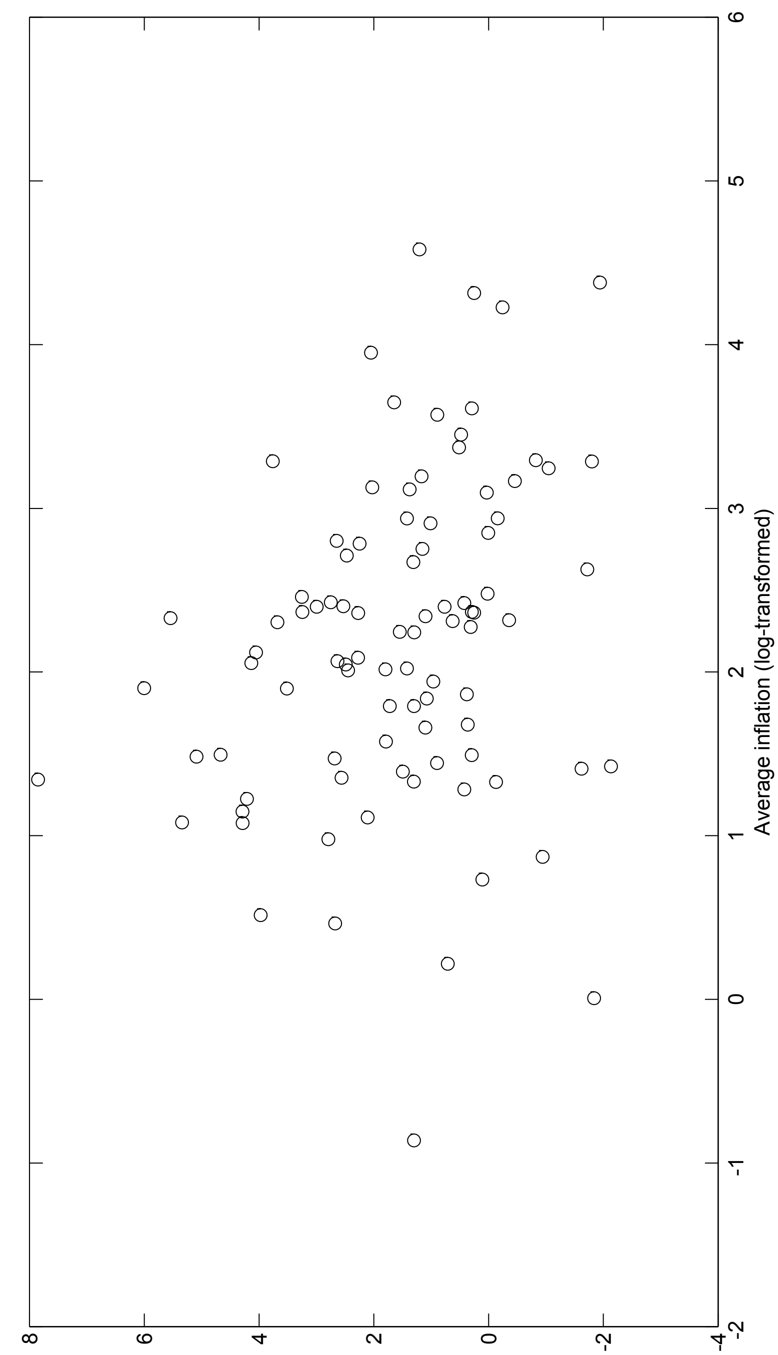


Figure 2: Partial Effect of Log-transformed Inflation on Growth

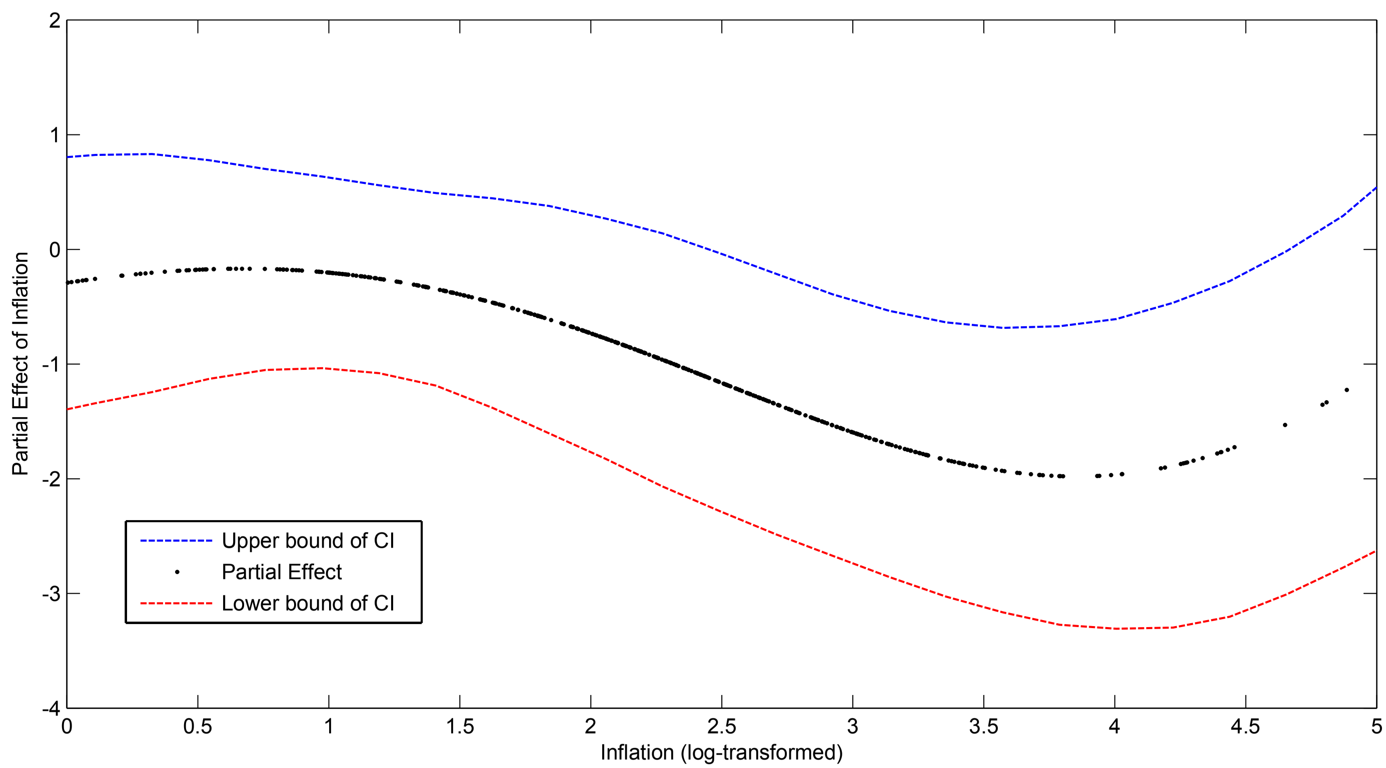


Figure 3: Partial Effect of Inflation on Growth

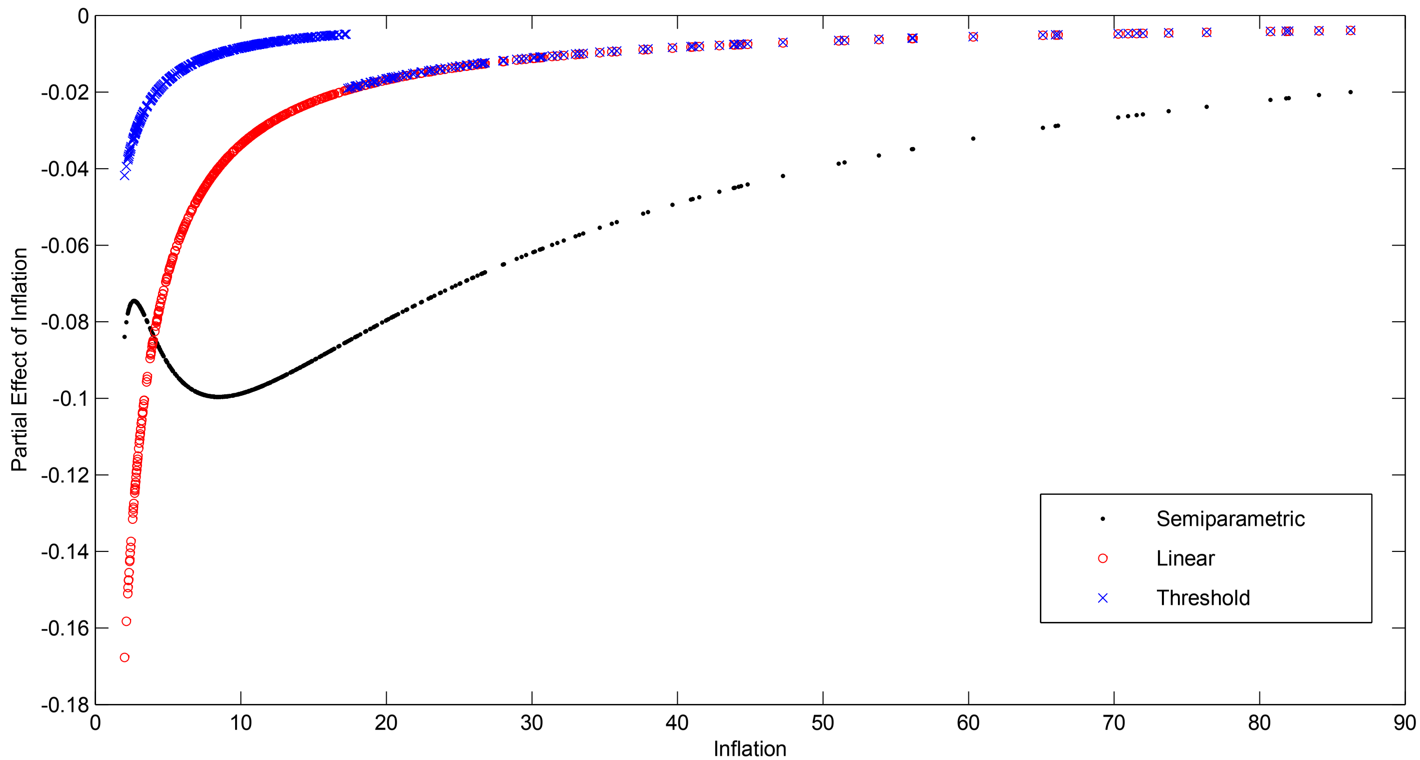


Figure 4: Distribution of the Partial Effect of Inflation on Growth across Countries

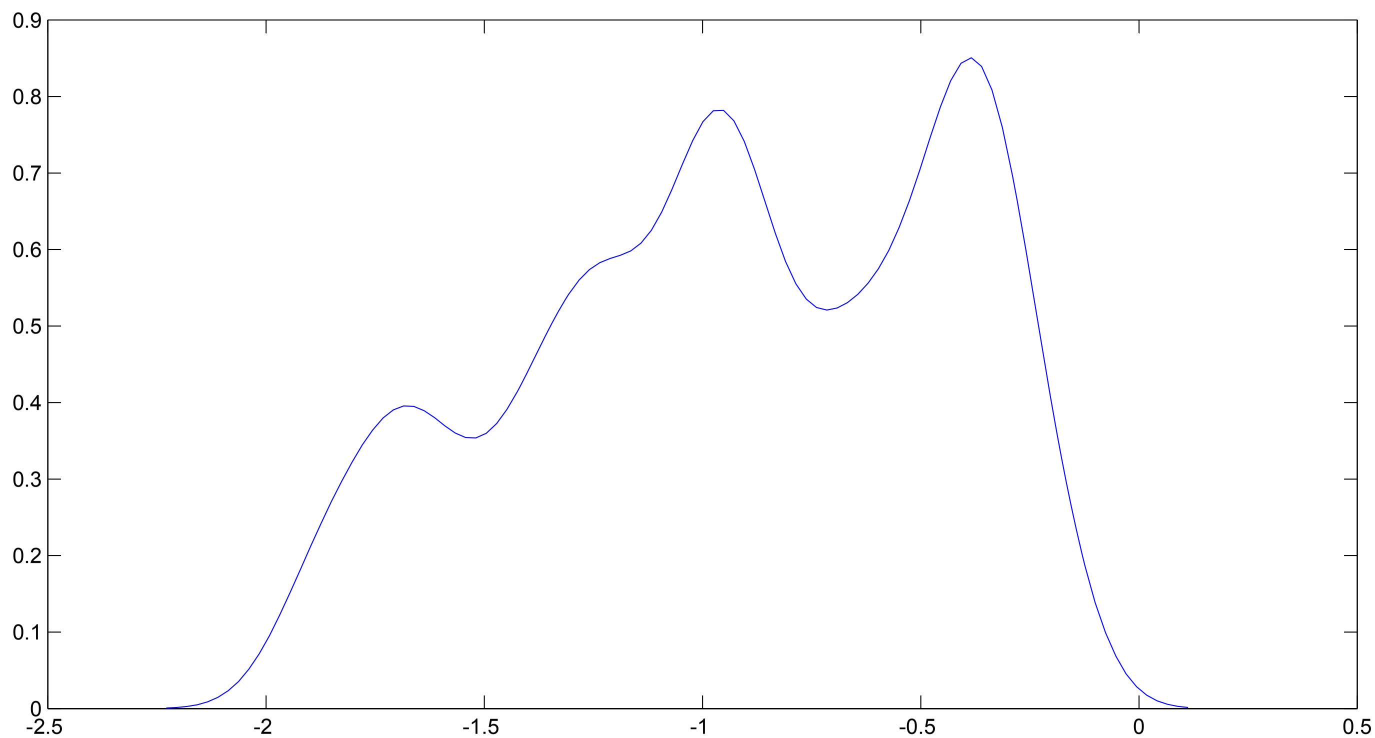


Figure 5: Distribution of the Partial Effect of Inflation on Growth across Countries over Time

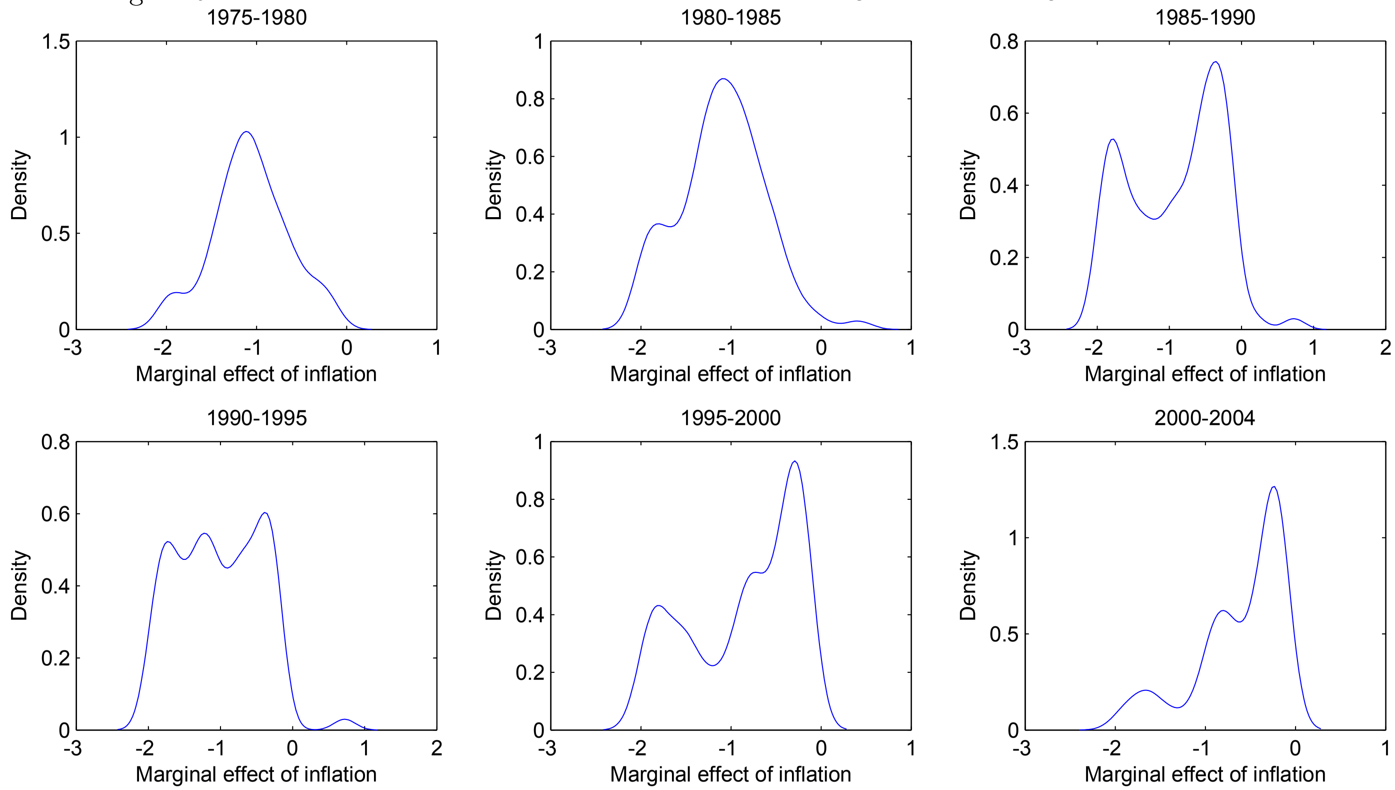


Figure 6: Partial Effect of Log-transformed Inflation on Growth in the Restricted Model

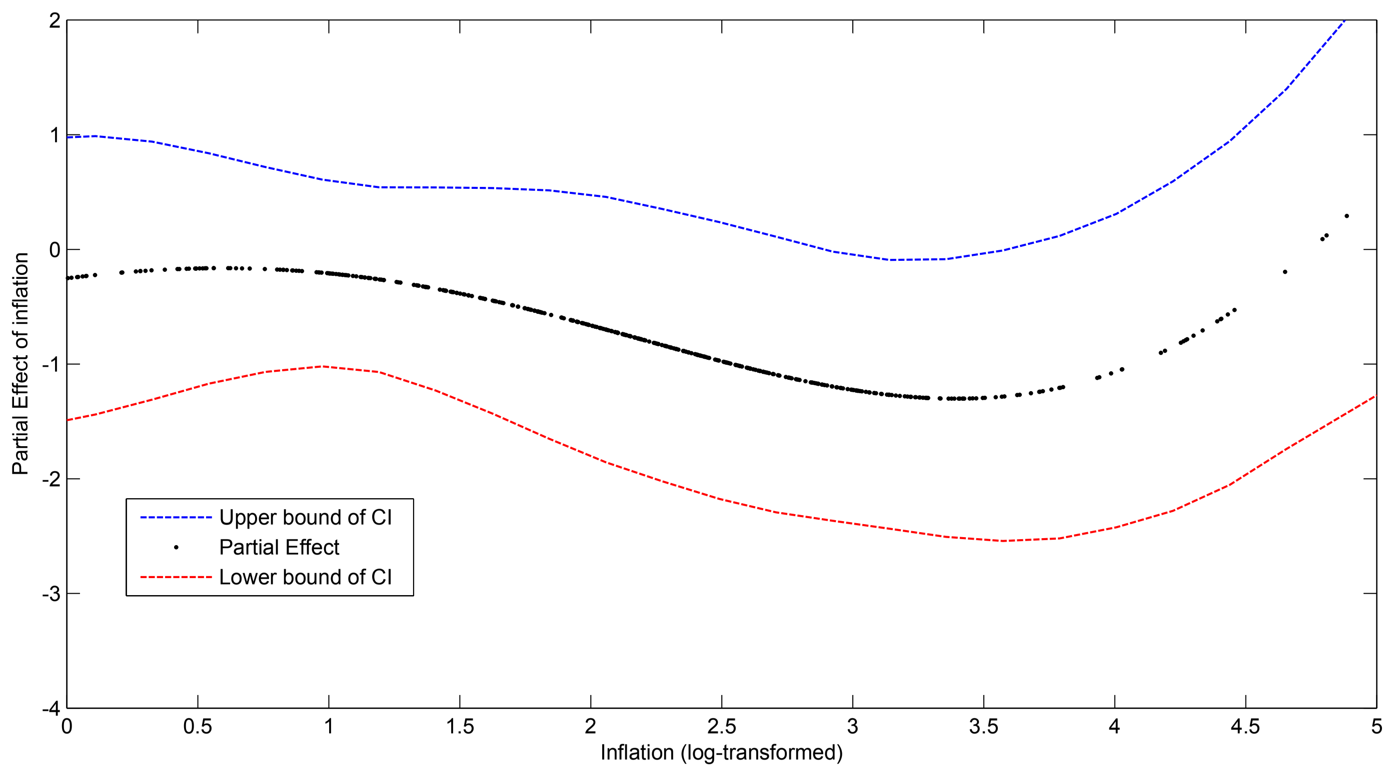
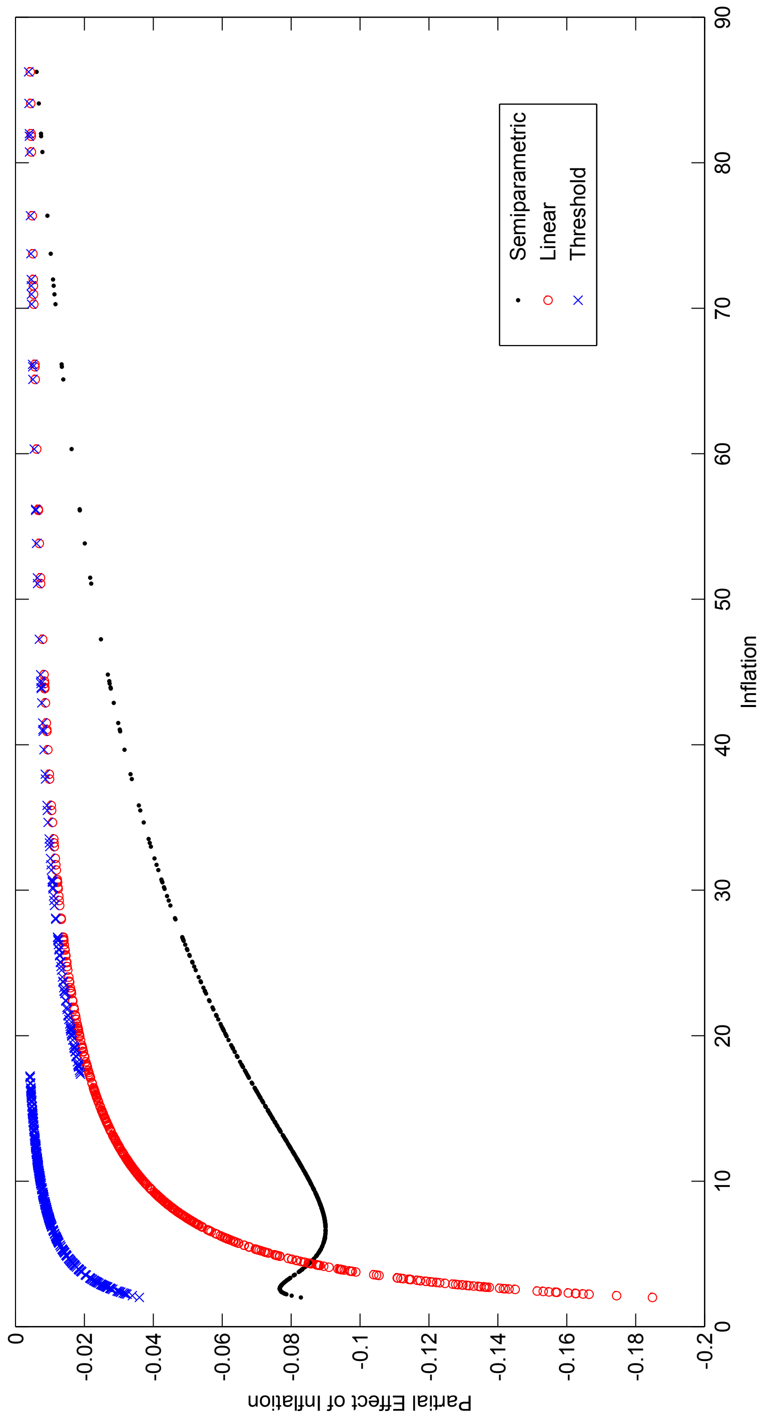


Figure 7: Partial Effect of Inflation on Growth in the Restricted Model



A List of Countries Included in the Sample

Algeria	Haiti	Peru
Argentina	Honduras	Philippines
Bahamas	Hong Kong	Poland
Bahrain	Hungary	Romania
Barbados	India	Rwanda
Bolivia	Indonesia	Samoa
Botswana	Iran	Saudi Arabia
Brazil	Israel	Senegal
Burkina Faso	Jamaica	Sierra Leone
Burundi	Jordan	Singapore
Cameroon	Kenya	Solomon Islands
Central African Republic	Korea (Republic of)	South Africa
Chad	Kuwait	Sri Lanka
Chile	Lesotho	St. Lucia
China	Madagascar	St. Vincent & Grenadines
Colombia	Malawi	Sudan
Congo Republic of	Malaysia	Suriname
Costa Rica	Mali	Swaziland
Cote d'Ivoire	Malta	Syria
Cyprus	Mauritius	Tanzania
Dominica	Mexico	Thailand
Dominican Republic	Morocco	Togo
Ecuador	Nepal	Tonga
Egypt	Netherlands Antilles	Trinidad & Tobago
El Salvador	Nicaragua	Tunisia
Ethiopia	Niger	Turkey
Fiji	Nigeria	Uruguay
Gabon	Pakistan	Venezuela
Gambia	Panama	Zambia
Ghana	Papua New Guinea	Zimbabwe
Guatemala	Paraguay	

B Bootstrap and Bias Correction

B.1 Fixed-design Wild Bootstrap

The bootstrap confidence intervals are obtained via the following steps:

1. For each $i = 1, \ldots, N$, and $t = 1, \ldots, T$, obtain the bootstrap error $u_{it}^* = \hat{u}_{it}\varepsilon_{it}$, where $\hat{u}_{it} = y_{it} - \hat{y}_{it}$, ε_{it} are $i.i.d$ $N(0, 1)$ across i and t, and $\hat{y}_{it}$ is fitted value of y_{it} obtained from Equation (1).

2. Generate the bootstrap sample $y_{it}^* = \widehat{y}_{it} + u_{it}^*$ for $i = 1, \ldots, N$, and $t = 1, \ldots, T$.

3. Given a bootstrap sample for the dependent variable as $\{(y_{it}^*, z_{it}, x_{it}),\ i = 1, \ldots, N,$ $t = 1, \ldots, T\}$ obtain the estimators of $g(.)$ and γ, and denote the resulting estimates by $\widehat{g}^*(.)$ and $\widehat{\gamma}^*$.

4. Repeat steps (1)-(3) a large number (B) of times to obtain the bootstrap samples $\widehat{g}_k^*(.)$ and $\widehat{\gamma}_k^*, k = 1, \ldots, B$. Let $Var^*(\widehat{g}(.))$ and $Var^*(\widehat{\gamma})$ denote the sample variances of $\widehat{g}_k^*(.)$ and $\widehat{\gamma}_k^*$, respectively.

5. Compute $T_{g,k}^* = \frac{|\widehat{g}_k^*(z) - \widehat{g}(z)|}{\{Var^*(\widehat{g}(z))\}^{1/2}}$ and $T_{\gamma,k}^* = \frac{|\widehat{\gamma}_k^* - \widehat{\gamma}|}{\{Var^*(\widehat{\gamma})\}^{1/2}}$ for $k = 1, \ldots, B$.

6. Use the upper α percentile of $T_{g,k}^*$ and $T_{\gamma,k}^*$, to estimate $c_{g,\alpha}$ and $c_{\gamma,\alpha}$.

7. Construct the $(1 - \alpha) \times 100\%$ bootstrap confidence intervals as follows:

$$\widehat{g}(z) \pm \{Var(\widehat{g}^*(z))\}^{1/2} c_{g,\alpha}$$
$$\widehat{\gamma} \pm \{Var(\widehat{\gamma}^*)\}^{1/2} c_{\gamma,\alpha}$$

B.2 Iterative Bootstrap Algorithm for Bias Correction

We search for a bias-corrected estimator for the linear component, γ, of the semi-parametric model in Equation (1). In order to find the bias-corrected estimator, we iterate over the bootstrap procedure. Steps for the iterative algorithm are as follows:

1. Given an estimate $\widetilde{\gamma}_j$ for γ, generate B bootstrap samples and calculate $\widetilde{\gamma}_j^b = B^{-1} \sum_{k=1}^{B} \gamma_k^*$ where γ_k^* is the estimate obtained from the kth bootstrap.

2. Define $\omega_j = \widehat{\gamma} - \widetilde{\gamma}_j^b$ where $\widehat{\gamma}$ is the initial estimate. Iterate until $\omega_j = 0$ by updating the estimate as follows: $\widetilde{\gamma}_{(j+1)} = \widetilde{\gamma}_j + \omega_j$. Set $\widetilde{\gamma}_1 = \widehat{\gamma}$ to start the iteration.