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Re-examining the threshold effects in the inflation–growth nexus with cross-sectionally dependent non-linear panel: Evidence from six industrialized economies

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ABSTRACT

This paper analyzes the empirical relationship between inflation and output growth using a novel panel data estimation technique, Panel Smooth Transition Regression (PSTR) model, which takes account of the non-linearities in the data. By using a panel data set for 6 industrialized countries that enable us to control for unobserved heterogeneity at both country and time levels, we find that there exists a statistically significant negative relationship between inflation and growth for the inflation rates above the critical threshold level of 2.52%, which is endogenously determined. Furthermore, we also control cross-section dependency by using the CD test modified to non-linear context and remedy cross-section dependency with Seemingly Unrelated Regression Equations through Generalized Least Squares (SURE-GLS) and newly proposed Common Correlated Effects (CCE) estimation techniques. We find that these methods change the critical threshold value slightly. The estimated threshold values from these estimation methods are 3.18% and 2.42%, respectively.

1. Introduction

The primary objective of macroeconomic policies is to attain high and sustainable output growth rates along with low and stable inflation rates. Therefore, the relationship between output growth rate and inflation rate is vital for policymakers. If growth and inflation rates are interrelated, then policymakers would like to control these variables depending on the structure of such relationship in order to achieve policy targets. Considering the importance of the inflation–growth relationship, it is not surprising that this topic has been one of the most widely studied topics in the economics literature.

The inflation–growth relationship has been investigated extensively on theoretical grounds (Arın and Omay, 2006).[1] Recent studies have shown that financial markets play a crucial role in non-linear interrelationship between inflation rate and output growth (Khan et al., 2001; Khan, 2002). Many studies have detected a threshold effect in both inflation–finance and inflation–growth relationships (Boyd et al., 1997; Khan et al., 2001; Bullard and Keating, 1995; Bruno and Easterly, 1998; Khan and Senhadji, 2001). The general model used to explain the non-linear and negative correlation in the inflation–growth nexus states that when inflation reduces real returns to savings, it exacerbates an informational friction afflicting the financial system. Such financial frictions may cause credit rationing, hence limit investment level, and reduce investment efficiency. These may cause an adverse effect on long run economic growth.

Previous empirical research on the interrelationship between inflation rate and growth rate used linear models (e.g., Barro, 1995, 1996; Levine and Renelt, 1992; Levine and Zervos, 1993). However, non-linearities in the inflation–growth nexus have attracted a huge interest of economists in recent years. These studies provide mixed results. Fischer (1993) uses a spline regression for analyzing this relationship and estimates inflation coefficients for the ranges of 0–10%, 10–40%, and over 40%. He finds a negative but diminishing effect of inflation on growth, indicating that the statistical significance of the inflation's negative effect on output growth rate decreases as inflation interval is extended. Sarel (1996) tests for a structural break in the inflation–growth regression, and finds that the coefficient estimate for inflation at rates below 8% is positive but statistically insignificant, but negative and significant above 8%. Barro (1996, 1997) finds that inflation does not significantly affect growth in countries where average annual inflation lies above 15% whereas in countries where inflation rate is below 15%,

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[1] However, there are new improvments in theoretical growth models. Omay and Baleanu (2009) have shown that the generalized solution of Romer's Technological change model is by using fractional calculus. Therefore, this new mathematical solutions can change the nature of the reduced form growth equation where this imporvement leads to reformalization of the inflation–growth nexus.

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inflation has a negative and a statistically significant effect on growth. Khan and Senhadji (2001) and Drukker et al. (2005) use unbalanced panel method in order to determine threshold effects for a larger sample of 140 and 138 countries, respectively. Khan and Senhadji (2001) find the thresholds to be around 1–3% for developed countries. Drukker et al. (2005) find two thresholds at 2.51% and 12.61% for industrialized countries. Hineline (2007) uses Bayesian Model Averaging (BMA)[2] approach to examine whether the inflation's effect on economic growth is robust to model uncertainty across alternative specifications. He finds that cross-sectional data provide little evidence of a robust inflation–growth relationship, even after allowing for non-linear effects. On the other hand, inflation becomes one of the more robust variables affecting growth when panel data with fixed effects model is used. His findings suggest that high inflation observations drive these results.[3]

Although previous researches provide some evidence that inflation has a negative effect on growth for different time intervals (Barro, 1991; Fischer, 1983, 1993; Bruno and Easterly, 1998), they are based either on linear models or non-linear models that are not adequate to model non-linearities properly. Particularly, inadequacy of these models stems, in part, from exogenous determination of the threshold levels. Moreover, the lack of consensus regarding the critical threshold level calls for a more advanced estimation techniques that allow for controlling unobserved heterogeneity at both country and time levels. In addition, estimating an accurate threshold level for the inflation–growth link would increase policymakers' ability to control macroeconomic stability. Therefore, this important issue has called forth a further investigation in parallel to the theoretical improvements in non-linear estimation techniques.

We contribute to this literature by applying panel smooth transition regression (PSTR) model, developed by González et al. (2005), which provides endogenous determination of the threshold levels. We believe that this model may give new insights for threshold effects in inflation–growth relationship with its advantages over old techniques like the panel threshold (PTR) model.[4] First, the PSTR model is a generalization of the PTR[5] model, which is used by Khan and Senhadji (2001) and Drukker et al. (2005) for finding appropriate threshold levels in the inflation–growth nexus. Second, although there seems to be a consensus in the literature about the effects of inflation on growth to be statistically insignificant or positive in low inflation regimes, and statistically significant and negative in high inflation regimes[6] the evidence on the threshold level is still mixed and scant.

In addition to estimating threshold values endogenously, another main contribution in this paper is that we propose new methodology to solve the cross-section dependency problem in a non-linear framework. There are numerous problems, such as heterogeneity, endogeneity and cross-section dependency in applying panel estimation techniques. The PSTR approach solves the heterogeneity and the endogeneity problems, as further discussed in Section 3. In order to solve the cross-section dependency problem, we generalize Pesaran's (2006) method to a non-linear framework, which makes use of cross-sectional averages to provide valid inference for stationary panel regressions with multifactor error structure. The estimated values by using these techniques show that there are no considerable differences between the original estimates and new estimates. Besides Pesaran's (2006) method, we use the traditional remedy, SURE-GLS (Seemingly Unrelated Regression Equations and Generalized Least Squares) which is feasible when the cross-section dimension N is smaller than the time series dimension T to remove the cross-section dependency. With all these contributions, we believe that the PSTR model will be the best method which obtains a specific inflation threshold level for selected industrialized countries. By applying this model to a sample of six[7] industrialized countries, we find that the critical threshold level for inflation above which it becomes harmful for growth is smaller than the previously suggested threshold levels. Our results are most comparable with those of Khan and Senhadji (2001).

The remainder of the paper proceeds as follows: Section 2 briefly reviews PSTR models and provides results of the linearity tests (homogeneity test) against STR type non-linearity, and the sequence of F tests for determining the order of logistic transition function. Section 3 proceeds with estimation of linear fixed effects panel model and the PSTR model. Section 4 provides a new technique which eliminates cross-section dependency from the non-linear panel estimation, and Section 5 concludes.

2. Specification and estimation of the PSTR model

Panel Smooth Transition Regression (PSTR) allows for a small number of extreme regimes where transitions in-between are smooth (González et al., 2005). Let us first consider the simplest case with two extreme regimes:

$$\Delta y_{it} = \mu_i + \beta_0' x_{it} + \beta_1' x_{it} F(s_{it};\gamma,c) + u_{it} \tag{1}$$

for $i = 1, ..., N$, and $t = 1, ..., T$, where N and T denote the cross-section and time dimensions of the panel, respectively. The dependent variable Δy_{it} is a scalar and denotes growth rates of GNP for the six industrialized countries. In this study, the independent variable k-dimensional vector x_{it} of time-varying exogenous variables are selected to be investment (I_t), openness to trade (O_t) and inflation (π_t), following Hineline (2007). μ_i represents the fixed individual effects, and finally u_{it} are the errors. Transition function $F(s_{it};\gamma,c)$ is a continuous function of observable variable s_{it}. It is normalized to lie between 0 and 1, which denote the two extreme values for regression coefficients. Following Granger and Teräsvirta (1993), González et al. (2005) consider the following logistic transition function:

$$F(s_{it};\gamma,c) = \left(1 + \exp\left(-\gamma \prod_{j=1}^{m} \left(S_{it} - c_j\right)\right)^{-1}\right) \text{with } \gamma > 0 \tag{2}$$

and $c_m \geq \ldots \geq c_1 \geq c_0$

where $c = (c_1, ..., c_m)'$ is an m-dimensional vector of location parameters, and the slope parameter γ denotes the smoothness of the transitions. A value of 1 or 2 for m, often meets the common types of variation. In cases where $m = 1$, low and high values of s_{it} correspond to the two extreme regimes. For $\gamma \to \infty$ the logistic transition function $F(s_{it};\gamma,c)$ becomes an indicator function $I[A]$, which takes a value of 1 when event A occurs and 0 otherwise. Thus, the PSTR model reduces to Hansen (1999)'s two-regime panel threshold model. Whereas for $m = 2$, $F(s_{it};\gamma,c)$ takes a value of 1 for both low and high values of s_{it}, minimizing at $(\frac{c_1 + c_2}{2})$. In that case, if $\gamma \to \infty$, $F(s_{it};\gamma,c)$ reduces into a three-regime threshold model. If $\gamma \to 0$,

[2] Bayesian Model Averaging is a technique designed to help account for the uncertainty inherent in the model selection process. By averaging over many different competing models, BMA incorporates model uncertainty into conclusions about parameters and prediction.

[3] However, this robustness is lost when estimation is carried out with instrumental variables (Hineline, 2007). We discuss endogeneity problem in the Data and results section of this paper.

[4] Threshold estimation technique is developed by Chan and Tsay (1998) and extended to panel data estimation by Hansen (1999, 2000).

[5] Khan and Senhadji (2001) estimate the most likely threshold level in a spline regression of inflation and growth which they have used exogenous determination of threshold value by using the Hansen (1999, 2000) technique. Thus, we shortly call their technique as panel threshold regression (PTR).

[6] See Fischer(1993), Sarel (1996), Khan and Senhadji (2001) and others.

[7] These six countries are Canada, France, Italy, Japan, the UK and the USA. This group constitutes G7 by adding Germany. Germany has some data problems due to the unification of East Germany and West Germany in the beginning of the 1990s. Because of this problem, we remove Germany from the sample. Thus, we can manage to organize a balanced panel. The method that we use in this study is adapted from González et al. (2005).

the transition function $F(s_{it};\gamma,c)$ will reduce into a homogenous or linear fixed effects panel regression for any value of m.[8]

The empirical specification procedure for the PSTR models consists of the following steps (González et al., 2005):

1. Without looking at the non-linearity features, specify an appropriate linear (homogenous) panel estimation model for the data under investigation.[9]
2. Test the null hypothesis of linearity against the alternative of the PSTR-type non-linearity. If linearity is rejected, select the appropriate transition variable s_{it} and the form of the transition function $F(s_{it};\gamma,c)$.
3. Estimate the parameters in the selected PSTR model.
4. Evaluate the model using diagnostic tests.
5. Modify the model if necessary.
6. Use the model for descriptive purposes.

Linearity tests are necessary for estimation of the PSTR models which contain unidentified nuisance parameters. To overcome this problem, one may replace the transition function $F(s_{it};\gamma,c)$ by its first-order Taylor expansion around $\gamma=0$ following Luukkonen et al. (1988). This will yield the following auxiliary regression:

$$\Delta y_{it}=\mu_i+\beta_0'^{*}x_{it}+\beta_1'^{*}x_{it}s_{it}+\ldots+\beta_1'^{*}x_{it}s_{it}^{m}+u_{it}^{*} \tag{3}$$

where $\beta_1'^{*}$, ..., $\beta_m'^{*}$ are the parameter vectors. Consequently, testing $H_0{:}\gamma=0$ in Eq. (1) is equivalent to testing the null hypothesis $H_0^{*}{:}\beta_1^{*}=\ldots=\beta_m^{*}=0$ in Eq. (3). This test can be done by LM type tests. Denoting the panel sum of squared residuals under H_1 as SSR_0 (which is the two-regime PSTR model), the corresponding F-statistic is then defined by:

$$LM_F=\frac{(SSR_0-SSR_1)/mk}{SSR_0/(TN-N-m(k+1))} \tag{4}$$

with an approximate distribution of $F(mk, TN-N-m(k+1))$. A set of candidate transition variables are tested to detect the one for which linearity is strongly rejected. Besides, linearity tests also serve to determine the appropriate order of m of the logistic transition function in Eq. (2). Teräsvirta (1994) proposed a sequence of tests for choosing between $m=1$ and $m=2$. Within PSTR framework, this testing sequence reads as follows: using the auxiliary regression (3) with $m=3$, test the null hypothesis $H_0^{*}{:}\beta_1^{*}=\beta_2^{*}=\beta_3^{*}=0$. If it is rejected, test $H_{03}^{*}{:}\beta_3^{*}=0$, then exclude $\beta_3^{*}=0$ and test $H_{02}^{*}{:}\beta_2^{*}=0|\beta_3^{*}=0$. and $H_{01}^{*}{:}\beta_1^{*}=0|\beta_2^{*}=\beta_3^{*}=0$.

$$\begin{aligned}&H_{03}^{*}:\beta_3^{*}=0\\&H_{02}^{*}:\beta_2^{*}=0|\beta_3^{*}=0\\&H_{01}^{*}:\beta_1^{*}=0|\beta_2^{*}=\beta_3^{*}=0\end{aligned} \tag{5}$$

These hypotheses are tested by the ordinary F tests, and denoted as F_3, F_2, and F_1 respectively. The decision rule is as follows: $m=2$ transition functions is selected for cases where p-value corresponding to F_2 is the smallest and $m=1$ transition function is chosen for other cases.

Once the transition variable and form of the transition function are selected, the PSTR model can be estimated by using non-linear least squares. The optimization algorithm can be disburdened by using good starting values. For fixed values of the parameters in the transition function, γ and c, the PSTR model is linear in parameters β_0' and β_1', and therefore can be estimated by using linear estimation techniques such as OLS. Hence, a convenient way to obtain reasonable starting values for the Non-linear Least Squares (NLLS) is to perform a two-dimensional grid search over γ and c, and select those estimates that minimize the panel sum of squared residuals. After parameter estimation, we perform a diagnostic check to evaluate the estimated PSTR model. Particularly, misspecification tests are used to test for parameter constancy and the remaining non-linearity (heterogeneity), as suggested by González et al. (2005). If the estimated model passes all misspecification tests, then the model can be used for descriptive purposes, meaning that the estimated model will not lead to biased estimates and spurious inference.

A related issue in panel estimations is cross-section dependency. Most of the panel data models assume that disturbances in panel models are cross-sectionally independent. However, cross-section dependence may arise for several reasons often, due to spatial correlations, spillover effects, economic distance, omitted global variables and common unobserved shocks. In the presence of cross-section dependence, it is well known that neglecting cross-section dependence can lead to biased estimates and produce misleading inference. In large panels, where N is a sizeable amount cross-section dependency is not a serious problem to control. In the empirical part of González et al. (2005) they apply their method to 565 US firms, hence they are not subject to cross-section dependency problem in this respect. But Pesaran (2004) pointed out that cross-section dependency continues to exist in large panels as well as small panels. Therefore, these two misspecification tests are sufficient when there is no cross-section dependency. Thus, we propose a diagnostic check for cross-section dependency for non-linear panel models following Pesaran (2004).

Because of these reasons, we apply a cross-section dependency (CD) test proposed by Pesaran (2004). Pesaran (2004) showed that his CD test can also be applied to a wide variety of models, including small/large N and T. Additionally, this simple diagnostic test does not require an a priori specification of connection or spatial matrix. CD test is based on simple average of all pair-wise correlation coefficients of the OLS residuals from the individual regressions in the panel:

$$\Delta y_{it}=\mu_i+\beta_i'x_{it}+u_{it} \tag{6}$$

where, on the time domain $t=1,2,\ldots,T$, for the cross-section units $i=1,2,\ldots,N$. x_{it} is a $k\times1$ vector of observed time-varying regressors. The individual intercepts, μ_i and slope coefficients β_i are defined on a compact set permitted to vary across i. For each i, $u_{it}\sim iid(0,\sigma_{i,u}^2)$, for all t although they could be cross-sectionally correlated.

The sample estimate of the pair-wise correlation of the residuals is:

$$\hat{\rho}_{ij}=\hat{\rho}_{ji}=\frac{\sum_{t=1}^{T}e_{it}e_{jt}}{\left(\sum_{t=1}^{T}e_{it}^2\right)^{1/2}\left(\sum_{t=1}^{T}e_{jt}^2\right)^{1/2}} \tag{7}$$

And the e_{it} is the OLS estimates of u_{it} defined by

$$e_{it}=\Delta y_{it}-\hat{\mu}_i-\hat{\beta}_i'x_{it} \tag{8}$$

The proposed CD test by Pesaran (2004) is:

$$CD=\sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \tag{9}$$

[8] There are two interpretations of the PSTR model which are clearly explained in González et al. (2005). First, it may be thought of as a linear heterogeneous panel model with coefficients that vary across individuals and over time. Second, the PSTR model can simply be considered as a non-linear homogenous panel model. Because of these reasons throughout the text, linear, homogenous and non-linear, heterogeneous are used interchangeably or one of them given in parenthesis if it's necessary. For more detailed discussion, see González et al. (2005).

[9] We follow Hineline (2007) for selecting appropriate variables for panel estimation where he used BMA method for selecting these variables.

CD test statistic has exactly mean zero for fixed values of T and N, under a broad class of panel data models. The CD test is based on a simple average of all pair-wise correlation coefficients of the NLLS residuals from the individual regressions in the smooth transition panel model:

$$\Delta y_{it} = \mu_i + \beta_0' x_{it} + \beta_1' x_{it} F(s_{it};\gamma, c) + u_{it} \tag{10}$$

and the e_{it} is the NLLS estimates of u_{it} defined by

$$e_{it} = \Delta y_{it} - \hat{\mu}_i - \hat{\beta}_0' x_{it} - F(\dot{s}_{it};\hat{\gamma},\hat{c})\hat{\hat{\beta}}_1' x_{it}$$
$$\text{Where } F(\dot{s}_{it};\hat{\gamma},\hat{c}) = \frac{1}{1+e^{-\hat{\gamma}(\dot{s}_{it}-\hat{c})}} \tag{11}$$

These are the estimated values of the slope (γ) and threshold (c) parameters. The dot on the transition variable means that it is selected from the linearity tests. In non-linear models, the definition of the residual is ambigous and can be defined in a number of different ways. The above representation is the definition of disturbance of the non-linear models analogous to the linear case. For the sake of clarity, we denote cross-section dependency test for the linear model as CD_{LM}^{L}, whereas CD_{LM}^{NL} denotes the same test for the non-linear model.

3. The empirical analysis: data and results

In this paper, we consider annual data from six industrialized countries (Canada, France, Italy, Japan, UK and US) which spans the period 1972–2005. We begin modeling the growth–inflation relationship by estimating a balanced panel data model for output growth (Δy_{it}) using inflation (π_{it}), investment (I_{it}), and openness (O_{it}) as explanatory variables. The output growth rate (Δy_{it}) is constructed as annual GDP growth rate. The inflation rate (π_{it}) is measured as percentage change of consumer price index, investment (I_{it}) is defined as the ratio of gross fixed capital formation to GDP, and openness O_{it} is defined as the ratio of exports of goods and services to GDP. All variables are extracted from the World Development Indicators (WDI) database. Any empirical analysis of the inflation's impact on economic growth has to control for the influence of other variables that are correlated with the rate of inflation. There are numerous studies which can be followed to choose such control variables (e.g., Khan and Senhadji, 2001; Drukker et al., 2005). But the most detailed and advanced technique is used by Hineline (2007). Hence, we follow Hineline (2007) in choosing control variables. Hineline (2007) uses different model specifications for inflation–growth relationship in order to investigate fragility of using inflation as a regressor in explaining growth. Hineline (2007) bases his analysis on the Bayesian Model Averaging (BMA) method.[10] In respect of the BMA results, Hineline (2007) finds that the probability of affecting growth is 100% for investment, 92% for openness to trade and 89% for inflation using the Khan and Senhadji (2001) estimation technique. In the light of these results, we decided to apply fixed effect panel data analysis and include investment and openness variables in our model specification in order to check the impact of other covariates.[11]

All the asymptotic theories for the STR models and also PSTR extension by González et al. (2005) are for stationary regressors. Therefore, the specification procedures described in the previous section rely on the assumption that the output growth, inflation, investment and openness to trade are $I(0)$ processes. In order to analyze stationarity properties of the data, prior to estimation of the linear model, we first test whether the data have a unit root by using panel unit root tests. It is well known that conventional unit root tests have low power if the true data generating process is non-linear. Hence, in addition to conventional panel unit root test IPS, we also applied the non-linear panel unit root test newly proposed by Ucar and Omay (2009), which we call as the UO test. The UO test has a good power when the series under investigation follow a non-linear process. A brief review of the UO test can be given as follows.

Let z_{it} be the panel exponential smooth transition autoregressive process of order one (PESTAR(1)) on the time domain $t=1,2,\ldots,T$ for the cross-section units $i=1,2,\ldots,N$. Consider z_{it} generated by the following PESTAR process with fixed effect parameter α_i:

$$\Delta z_{it} = \alpha_i + \phi z_{it-1} + \gamma_i z_{it-1}\left[1-\exp\left(-\theta_i z_{it-d}^2\right)\right] + \varepsilon_{it} \tag{12}$$

where $d \geq 1$ is the delay parameter and $\theta_i \geq 0$ represents the speed of revision for all units; ε_{it} is a serially and cross-sectionally uncorrelated disturbance term with zero mean and variance σ_i^2.

Following previous literature, Ucar and Omay (2009) set $\phi_i=0$ for all i and $d=1$ which gives specific PESTAR(1) model:

$$\Delta z_{it} = \alpha_i + \gamma_i z_{it-1}\left[1-\exp\left(-\theta_i z_{it-d}^2\right)\right] + \varepsilon_{it} \tag{13}$$

Non-linear panel data unit root test based on regression (13) with augmented lag variables in empirical application is simply to test the null hypothesis $\theta_i=0$ for all i against $\theta_i \geq 0$ for some i under the alternative.

However, direct testing of the null hypothesis is problematic since γ_i is not identified under the null. This problem can be solved by taking first-order Taylor series expansion to the PESTAR(1) model around $\theta_i=0$ for all i. Hence the obtained auxiliary regression is given by:

$$\Delta z_{it} = \alpha_i + \delta_i z_{it-1}^3 + \varepsilon_{it} \tag{14}$$

where $\delta_i=\theta_i\gamma_i$. In empirical application Eq. (14) is augmented by lagged variables of dependent variables by using AIC and SIC criteria. Based on Eq. (14), the hypothesis for unit root testing is

$$H_0: \delta_i = 0, \quad \text{for all } i, \quad (\textit{Linear Nonstationary})$$
$$H_0: \delta_i < 0, \quad \text{for all } i, (\textit{Non}-\textit{linear Stationary})$$

The UO test is constructed by standardizing the average of individual KSS statistics across the whole panel. First, the KSS test for the *ith* individual is the t-statistics for testing $\delta_i=0$ in Eq. (14) defined by:

$$t_{i,NL} = \frac{\Delta z_i' M_t z_{i,-1}^3}{\hat{\sigma}_{i,NL}\left(z_{i,-1}' M_t z_{i,-1}\right)^{3/2}}$$

where $\hat{\sigma}_{i,NL}^2$ is the consistent estimator such that $\hat{\sigma}_{i,NL}^2=\Delta z_i' M_t z_i/(T-1)$, $M_t = I_T - \tau_T(\tau_T'\tau_T)^{-1}\tau_T'$ with $\Delta z_i = (\Delta z_{i-1}, \Delta z_{i-2}, \ldots \Delta z_{i-T})'$ and $\tau_T = (1, 1, \ldots, 1)$.

Furthermore, when the invariance property and the existence of moments are satisfied, the usual normalization of $\overline{t}_{NL}$ statistic yields as follows[12]:

$$\overline{Z}_{NL} = \frac{\sqrt{N}\left(\overline{t}_{NL} - E\left(t_{i,NL}\right)\right)}{\sqrt{\left(t_{i,NL}\right)}}$$

[10] This analysis showed that inflation does not give robust results when cross-sectional or fixed effect instrumental methods are used, but it does when fixed effect panel data method is used. Besides, in this study, investment and openness are found to be the most robust variables in the fixed effect panel data method.

[11] There are arguments, however, that there are country specific factors that cannot be ignored, which suggests the use of the fixed effects methods (Knight et al. (1993) and Hineline (2007)).

[12] Until here z represents variable, hereafter it is z statistics.

where $\overline{t}_{NL} = N^{-1}\sum_{i=1}^{N} t_{NL}$; $E(t_{i,NL})$ and $\mathrm{var}(t_{i,NL})$ can be found in Table 1 of Ucar and Omay (2009). The test statistics are:

The UO and IPS tests reject the null hypothesis of unit root at 1% and 10% significance levels in the examined series. As regards to openness to trade O_{it}, the IPS test failed to reject the null hypothesis of unit root when intercept and trend are included. This result may be due to the fact that the IPS test has a low power against non-linear stationary process. From the non-linear panel unit root test, we can conclude that all the variables in the study are $I(0)$. From both linear and non-linear panel unit root tests, we can conclude that the variables in the study are $I(0)$. The results of the linear fixed effect panel data are presented below:

The results in Table 2 coincide one-to-one with Hineline (2007)'s study. Inflation variable has a statistically significant and negative effect on growth. Investment and openness to trade are also found to have a statistically significant but positive effect on growth. Fixed effects and time dummies have been included (but not reported) to control for unobserved heterogeneity at country and time levels. The fixed effect linear panel data analysis shows that we have obtained the right model specification in order to estimate the PSTR model, as the linear model specification constitutes a very important stage in the identification procedure.

After estimating the linear model, we apply the LM_F test of linearity, described in Section 2, using lagged inflation as transition variables. We only test linearity of the coefficients of π_{it} (inflation), I_{it} (investment, or gross capital formation as a percentage of GDP) and O_{it} (openness, or exports to GDP ratio), assuming that their macroeconomic effects on GDP growth do not differ across countries. Restricting coefficients of some variables to be constant in the PSTR model has no effect on the distribution theory (González et al. (2005)). For this purpose, LM_F test for $m=1$, 2, and 3 are applied to auxiliary regression in Eq. (3) and the following results are obtained (Table 3).

Linearity is significantly rejected for the first lag of the inflation rate for both models 1 and 2. By checking out the smallest p values, we find that the lag order 1 is an appropriate transition variable and the most suitable transition function for this selection is $m=1$. This shows that the inflation–growth nexus exhibits different dynamics in both regimes, suggesting that this relationship is non-linear.

Following these linearity tests, we apply a sequence of F tests in order to check whether the order m is one or not. The results of the specification test sequence are given in the table below:

The decision rule is as follows: $m=2$ transition function is selected for the cases where p-value corresponding to F_2 is the smallest and $m=1$ transition function is chosen for all other cases. The results of the specification test sequence in Table 4, point out that for both models 1 and 2, F_1 *has* the strongest rejection which means that $m=1$ transition function is selected. In the next step, we start a grid search, discussed in Section 2, in order to obtain the initial values for the non-linear fixed effect panel estimation. The estimates of the two-regime PSTR model are as follows:

The choice of logistic function as a transition function suggests that the relationship between the inflation rate and output growth rate varies considerably with the past values of the inflation rate. The logistic transition function defines two different regimes. These regimes can be defined with respect to the past values of π_{it} relative to the estimated threshold values $c=2.518$ and 3.460. When the transition variable (i.e. π_{it}) takes on values less than the estimated threshold values (approximately 2.52% for model 1 and 3.46% for model 2), the transition function approaches zero, and hence the coefficients of inflation rate, investment and openness are given by $\beta_{\pi_{it}}, \beta_{I_{it}}, \beta_{O_{it}}$, respectively. We call this regime as low inflation regime. When the transition variable exceeds specified threshold variables, however, the transition function takes on value one, and hence, the coefficients of variables of interest are given by $\beta_{\pi_{it}}+\tilde{\beta}_{\tilde{\pi}_{it}}$, $\beta_{I_{it}}+\tilde{\beta}_{\tilde{I}_{it}}$, and $\beta_{O_{it}}+\tilde{\beta}_{\tilde{O}_{it}}$, respectively. We call this regime as a high inflation regime.

There are many observations lying on both sides of these parameters clearly implying the existence of two distinct regimes. The results suggest that parameter estimates are quite different for each regime. Therefore, the PSTR model implies asymmetric responses of output growth to covariates. Furthermore, country specific averges of inflation rate in the sample period are 2,525, 2,579, 2.941, 1.893, 2.821, and 2.489 for Canada, France, Italy, Japan, UK and US, respectively. Therefore, we can conclude that the estimated threshold values are appropriate.[13]

The estimated values of the location (threshold) parameter c and transition parameter γ as well as the graph of the estimated transition

Table 1
Non-linear and linear panel unit root tests without cross-section dependency.

	Ucar–Omay (UO)	IPS
	$\overline{t}_{NT}$	$\overline{t}_{NT}$
Intercept		
Δy_{it}	−3.624*	−3.857*
π_{it}	−2.825*	−2.869*
O_{it}	−2.143***	−2.032**
I_{it}	−2.091***	−2.002**
Intercept ± trend		
Δy_{it}	−4.275*	−4.298**
π_{it}	−3.506*	−3.528**
O_{it}	−2.591***	−2.535
I_{it}	−3.068*	−3.107***

Notes: asymptotic critical values of $\overline{t}_{NT}$ for UO test statistics at 1%, 5% and 10% significance levels are −2.44, −2.21, and −2.08 and for trend-intercepts are −2.94, −2.72, and −2.57. For intercept only, the values are taken from Table 2 of Ucar and Omay (2009, p: 6). Asymptotic critical values of t-bar statistics at 1%, 5% and 10% significance levels are −2.20, −1.95 and −1.85 and for the trend-intercepts are −4.50, −3.35, and −3.02. These values are taken from Table 2 IPS (2003, p 61–62). *, **, and *** denote significance at 1%, 5% and 10% levels, respectively. Besides, optimal lag length in these tests were selected using AIC with maximum lag order of 8.

Table 2
Estimation results of linear (homogeneous) panel.

$\Delta y_{it} = -0.630_{(0.091)}\pi_{it} + 0.079_{(0.036)}I_{it} + 0.488_{(0.064)}O_{it}$	Model 1 $CD^L_{LM}=10.737$ (0.000)
$\Delta y_{it} = -0.323_{(0.093)}\pi_{it}$	Model 2 $CD^L_{LM}=9.873$ (0.000)

Note: the values under the coefficient estimates are standard error. Except $I_{i,t}$, all the variables are significant at the 1% significance level.
$I_{i,t}$ is significant at the 5% level.

Table 3
Linearity (homogeneity) tests.

Transition variable	$m=1$	$m=2$	$m=3$
Model 1 (π_{it})	20.438	14.329	13.671
	(0.000)	(0.000)	(0.000)
Model 2 (π_{it})	86.912	47.693	67.610
	(0.000)	(0.000)	(0.000)

* The values in the parentheses are p values.

Table 4
Sequence of linearity (homogeneity) tests for selecting m.

Transition variable	H_{01}	H_{02}	H_{03}
Model 1 (π_{it})	3.679	0.586	0.988
	(0.013)	(0.624)	(0.399)
Model 2 (π_{it})	9.897	4.428	3.165
	(0.001)	(0.036)	(0.076)

* The values in the parentheses are p values.

[13] We also estimate country by country LSTR models, but these estimates are carried out using 35 data points which is very insufficient to handle a time series analyses. The estimated threshold values are close to those reported here and are available upon request.

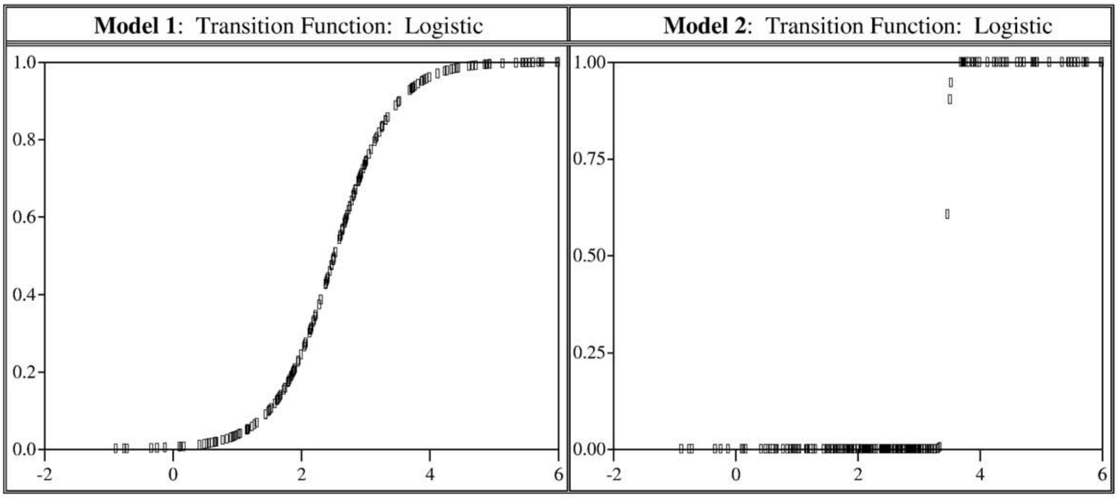

Fig. 1. Transition functions with respect to transition variable for models 1 and 2. * y axis is the transition function $F(s_{it}; \gamma, c)$ and the x axis is the transition variable. For models 1 and 2 the transition variable is the first lag of inflation.

function as a function of π_{it-1} provides useful information about the features of the transition itself and the interpretation of the model. Fig. 1 shows the transition functions. As the graph of the transition functions suggest,the change between regimes is quite gradual for the model 1 and moderate for the model 2.[14] These are also indicated by the estimated transition parameters $\gamma = 3.308$ and 69.052, respectively for models 1 and 2. The estimated threshold values of $c = 2.518$ and 3.460 points to the half way of the transition, meaning that when $\pi_{it-1} = c$, $F(s_{it};\ \gamma,\ c) = 1/2$. It indicates the half-way point between the low inflationary and high inflationary regimes for selected industrialized countries.

The inflation threshold value is very close to the threshold value of Khan and Senhadji (2001) who use yearly data. They find the threshold value for industrialized countries as 3%. The problem with the 5 year averaged data stems from the fact that there are only a few observations with an inflation rate below the threshold level of industrial countries. From Fig. 1, we see that this problem is overcome by using the annual data. Though the majority of observations lie in either one of the extreme regimes, a number of them are located in-between.

For low inflation regimes, inflation coefficients are found to be −0,150 and 0,140 in the 1st and 2nd models, respectively. These estimates are statistically insignificant. For high inflation regime, on the other hand, the 1st and 2nd models yield inflation coefficient estimates of −0.729 and −0.327 respectively. Coefficient estimates in both models are found to be statistically significant at a significance level of 1%. These results are consistent with Hineline (2007), who calculated BMA probabilities of low and high inflation regimes for the fixed effect panel data method by the means of a threshold model. Hineline (2007) determines that inflation coefficient is not a robust estimator in low inflation regimes, with a probability of as low as 0.09 whereas on the other hand, BMA the probability of inflation coefficient is found to be as high as 0.84 for the high inflation regimes.[15] Indeed, the most widely-accepted relationship in the literature is that inflation has an adverse effect on economic growth only after it crosses a certain threshold level, below which it has a positive effect on growth (Singh and Kalirajan, 2003). Sarel (1996) allows for a structural break and determines that inflation rates below 8% do not affect growth, but higher inflation rates do. Fischer (1993) uses a spline regression to estimate coefficients of inflation for the ranges of 0–10%, 10–40% and over 40%, and finds a negative but diminishing effect on growth.

Furthermore, we estimate the threshold value endogenously by taking advantage of the PSTR modeling approach (Table 5). The endogenously obtained threshold values from model 1 and model 2 are 2.518 and 3.460, respectively for inflation. Threshold values are estimated at a significance level of 1% for models 1 and 2. Threshold values are decreasing significantly as new explanatory variables are introduced. This finding leads us to conclude that the highest threshold value for inflation is 3.460. This result is absolutely opposite to Khan and Senhadji (2001) and Drukker et al. (2005) findings.[16] When we fix the threshold values in our estimation,[17] we find that the coefficient estimates and their significance levels are affected, but the effect is only minor. In this study, we concentrate on finding the threshold levels, as the estimation results show that the exogenous determination of threshold levels does not permit to establish a precise threshold level. If the threshold is estimated exogenously in a band out of the estimation process, this can lead to an error. For example, our estimated threshold values for the first and second models change approximately by 1% as new explanatory variables are included. If we fix the threshold value to 3.00 (an integer number), we find approximately the same coefficient estimates. This finding indicates a similar relationship structure that has been previously identified. In low inflation regimes, coefficient estimates of the inflation rate are insignificant and low compared to high inflation regimes, and high inflation regime has significant coefficient estimates. Although these values are not exact, one may think that these are the true model and precise threshold levels. The methodology of Khan and Senhadji (2001) and Drukker et al. (2005) does not permit to see this effect, because of the exogenous determination of the threshold values. Moreover, if variables that are found to be robust in the empirical

[14] Regime change is seemed to be discontinuous in Fig. 1 model 2, but this is not a problem for the STR modeling. The main purpose of STR modeling is to set a slow change in regimes. For example in González et al. (2005) they state their explanations "A clear majority of observation lie either one of the extreme regimes, but there is also a number of them located in-between". They also find a high speed of regime change with respect to our slope parameter, gamma. Our gamma parameter estimates for models 1 and 2 are 3.308 and 69.052, respectively, whereas González et al. (2005) estimate is 118.77. See also Béreau et al. (2010).

[15] Along with BMA probabilities, Hineline (2007) notes that coefficient estimates are negative for both regimes; statistically insignificant in low regimes (−0.059) because of the low BMA probability, but significant in high regimes (−0.026) due to the high BMA probability.

[16] As explained in Khan and Senhadji (2001) only variables that were found to be robust in the empirical growth literature were included in regression equation linking inflation to growth. Furthermore, their inclusion does not significantly change the results. In fact, the threshold values remain the same in Khan and Senhadji (2001).

[17] We have given constant numbers to gamma and c, and change c in order to see the effects of c on the parameter estimates. These results are available upon request.

Table 5
Estimation results of two-regime PSTR models.

Dependent variable Δy_{it}		
Coefficients	Model 1	Model 2
$\beta_{\pi_{it}}$	−0.150	0.140
	(0.284)	(0.140)
$\beta_{I_{it}}$	0.418***	–
	(0.089)	
$\beta_{O_{it}}$	0.050	–
	(0.033)	
$\tilde{\beta}_{\tilde{\pi}_{it}}$	−0.579*	−0.467***
	(0.347)	(0.107)
$\tilde{\beta}_{\tilde{I}_{it}}$	0.043	–
	(0.053)	
$\tilde{\beta}_{\tilde{O}_{it}}$	−0.010	–
	(0.043)	
γ	3.308	69.052
	(4.453)	(388.916)
c	2.518***	3.460***
	(0.576)	(0.132)

(*) 10% significance level, (**) 5% significance level, and (***) 1% significance level.
The values in the parentheses are standard deviations.

Table 6
Misspecification test.

Models	1		2	
Remaining non-linearity (heterogeneity)				
Transition variable used	π_tHAC	π_t	π_tHAC	π_t
$m=1$	1.51	5.07	0.00	0.00
	(0.67)	(0.00)	(0.97)	(0.99)
$m=2$	4.16	2.81	1.14	2.57
	(0.65)	(0.00)	(0.56)	(0.03)
$m=3$	9.18	2.19	3.93	2.50
	(0.42)	(0.01)	(0.26)	(0.02)
Parameter constancy				
Transition variable used	t HAC	T	t HAC	t
$m=1$	3.95	1.51	2.22	1.63
	(0.26)	(0.16)	(0.13)	(0.17)
$m=2$	7.17	4.16	2.84	2.72
	(0.30)	(0.00)	(0.24)	(0.02)
$m=3$	13.26	2.95	3.51	1.67
	(0.15)	(0.00)	(0.31)	(0.13)
Cross-section dependency test CD_{LM}^{NL}				
$CD_{\text{non-linear}}$	8.31			8.95
	(0.00)			(0.00)

* The values in the parentheses are p values.
* HAC values are robust versions of the standard test.

inflation–growth literature are introduced into the model, the threshold level changes. Still, we can conclude that the threshold level is *i*.

The results in Table 6 suggest that according to the standard tests, the model does not completely capture non-linearity in regression coefficient across countries, while some indication of the time-variation in the parameters is found as well. This finding complies with results of Lundbergh et al. (2003), Huang and Chang (2005), Telatar and Hasanov (2009), who found that both structural change and non-linearity might govern the dynamics of many economic variables. However, as the robustness tests indicate, no evidence is found for remaining non-linearity and parameter instability. Thus, based on the robustness tests, we conclude that the two-regime model is adequate.[18] Both models pass misspecification tests proposed by González et al. (2005), but, they fail to pass CD_{LM}^{NL} test discussed in Section 2. Hence, we cannot use these models for descriptive purposes.

Two important issues, namely, endogeneity problem and cross-section dependency must also be addressed. It is well known that when the inflation is not an exogenous variable in the growth–inflation regression, the coefficient estimates may be biased. This is a serious problem for the related estimations. The estimation methods used in Khan and Senhadji (2001) and Drukker et al. (2005)[19] have not been extended to the standard econometric methods of handling simultaneity like the method that we use here. Thus, they postpone this issue. Khan and Senhadji (2001) stated that the seriousness of this problem will depend, to a large extent, on whether the causality runs mainly from inflation to growth, in which case the endogeneity problem may not be serious, or the other way around, in which case a bias may be present. Fischer (1993) found out that causality is more likely to run predominantly from inflation to growth. Besides, Andres and Ignacio (1997) use instrumental variables in a study of OECD countries and find the causation runs from inflation to growth. On the other hand, Fouquau et al. (2008) apply IV estimation technique to the PSTR model; they conclude that the PSTR estimation technique reduces the potential endogeneity bias. Moreover, Hineline (2007) states that the aggregate supply shocks may drive inflation and output in the opposite directions. In this case, the direction of causality is reversed and the regressions within the framework of the inflation–output relationship simply detect supply shocks. Instead of using IV estimation techniques, he proposes a method, which uses a proxy for aggregate supply shocks in estimating growth regression. One of the proposed potential variables is terms of trade and the other is time dummy. Furthermore, in order to eliminate cross-section dependency, which may occur because of spillover effects or common shocks, one may use spatial matrices or common factors in the estimation of the model. These common factors can proxy the aggregate supply shocks. Therefore, eliminating cross-section dependency by including common factors into the model estimation may eliminate the endogeneity bias which may be observed in the growth–inflation nexus. From these discussions, we can conclude that the main problem is cross-section dependency, thus, we concentrate on this problem at the rest of the study.

4. Cross-section dependency

The test of the panel unit root explained in the previous section was based on the assumption of independence over the cross-section units. However, we see from the diagnostic check that this assumption is violated. To overcome the cross-section dependency problem, we implemented sieve bootstrap approach which is very well outlined in Ucar and Omay (2009). The test results for the UO and IPS with Sieve bootstrap is given in the table below:

As can be seen from Table 7, the UO and IPS tests suggest that growth Δy_{it} and inflation π_{it} variables are stationary for intercept and intercept + trend regression models. As regards to investment I_{it} and openness to trade O_{it}, the IPS test failed to reject the null hypothesis of the unit root when intercept and trend are included. This result may be due to the fact that the IPS test has a low power against non-linear stationary process. From the non-linear panel unit root test, we can conclude that all the variables in the study are $I(0)$. Hence, we can proceed to remedy cross-section dependency.

In the presence of cross-sectionally correlated error terms, traditional OLS-based estimations are inefficient and invalidate

[18] From the linearity test, we can conclude that our sample countries have a single threshold value. This finding is consistent with Li (2007). Li (2007) has found out that developed countries have a single threshold in determining the inflation–growth relationship, whereas developing countries have two thresholds.

[19] Drukker et al. (2005) state that “In cross-sectional growth literature, some of these variables are treated as endogenous and instrumental (IV) estimates are used. The method used in this paper has not yet been extended to the case of instrumental variables. This paper assumes that any endogenous component are perfectly correlated with fixed effects, and therefore controlled by our fixed effect estimation procedure”. Moreover, they excluded initial income from their growth regression to avoid the endogeneity problem.

Table 7
Non-linear and linear panel unit root tests with cross-section dependency.

	Ucar–Omay (UO)		IPS	
	T-bar	*p*_value	*t*-bar	*p*_value
Intercept				
Δy_{it}	−2.708	0.000	−3.682	0.000
π_{it}	−1.924	0.076	−1.964	0.057
O_{it}	−1.990	0.096	−1.967	0.093
I_{it}	−1.950	0.090	−1.965	0.072
Intercept ± trend				
Δy_{it}	−3.244	0.001	−4.107	0.000
π_{it}	−2.336	0.005	−2.947	0.013
O_{it}	−2.361	0.060	−2.437	0.251
I_{it}	−2.341	0.015	−2.632	0.105

Notes: *t*-bar statistic was computed by bootstrapping with 2000 replications and the *p* value results are byproducts of these bootstraps.

much inferential theory of the panel data models as discussed above. The traditional remedy, SURE-GLS (Seemingly Unrelated Regression Equations and Generalized Least Squares) is feasible when the cross-section dimension N is smaller than the time series dimension T. The standard approach is to treat the equations from the different cross-section units as a system of seemingly unrelated regression equations and then estimate the system by Generalized Least Squares technique. If both of these dimensions are same, the disturbance covariance matrix will be rank deficient. In our case, we have the opportunity to apply SURE-GLS method to remedy cross-section dependency. However, when the non-zero covariance is between the errors of different cross-section units due to common omitted variables, it is not apparent that SURE-GLS is always the correct approach (Coakley et al., 2002). For this reason, we search for a more efficient method which is not subject to these kinds of problems. Therefore, we use Pesaran's (2006) approach, which suggests a method that makes use of cross-sectional averages to provide valid inference for stationary panel regressions with multifactor error structure. In this section, we extend this work to non-linear framework. We suggest a new approach by noting that the linear and non-linear combinations of the observed factors can be well approximated by cross-section averages of the dependent, independent and state dependent variables. The estimation procedure has the advantage that it can be computed by least squares estimation of the auxiliary regressions where the observed regressors are augmented with cross-sectional averages of dependent variables, individual specific regressors and state dependent variables. This leads to a new set of estimators, which is mentioned in Pesaran (2006), referred to as the Common Correlated Effects (CCE) estimators, that can be computed by running smooth transition panel regressions augmented with cross-section averages of the dependent, independent and state dependent variables. CCE procedure is applicable to panels with single or multiple unobserved factors so long as the numbers of the unobserved factors is fixed.

Consider the following non-linear model with a single factor:

$$y_{it} = \mu_i + \beta_i' x_{it} + F(s_{it}, \gamma, c)\,\tilde{\beta}_i' x_{it} + u_{it} \tag{15}$$

where

$$F(s_{it}, \gamma, c) = \frac{1}{1 + e^{-\gamma(s_{it} - c)}},$$
$$u_{it} = \varphi_i f_t + \varepsilon_{i,t},$$
$$x_{it} = \delta_i \tilde{f}_t + v_{it}$$

Notice here that f_t and $\tilde{f}_t$ are different factor variables that affect dependent, independent and state dependent variables, respectively.

Now suppose that u_{it} and x_{it} specifications are plugged into original Eq. (15). Thus, we have:

$$y_{it} = \mu_i + \beta_i'\delta_i\tilde{f}_t + F(s_{it}, \gamma, c)\,\tilde{\beta}_i'\delta_i\tilde{f}_t + \beta_i v_{it} + F(s_{it}, \gamma, c)\,\tilde{\beta}_i' v_{it} + \varphi_i f_t + \varepsilon_{it} \tag{16}$$

$\tilde{f}_t$ can be removed by using proxy variable, $\overline{x}_t$ where $\overline{x}_t = N^{-1}\sum_{i=1}^{N} x_{it}$ which can be obtained through taking the average of x_{it}: $\overline{x} = \overline{\delta}\tilde{f}_t + \overline{v}_t$ which implies that $\tilde{f}_t = \frac{\overline{x}_t - \overline{v}_t}{\overline{\delta}}$. Substituting this into Eq. (16) we obtain:

$$y_{it} = \mu_i + \beta_i'\delta_i\left(\frac{\overline{x}_t - \overline{v}_t}{\overline{\delta}}\right) + F(s_{it}, \gamma, c)\,\tilde{\beta}_i'\delta_i\left(\frac{\overline{x}_t - \overline{v}_t}{\overline{\delta}}\right) + \beta_i v_{it} + F(s_{it}, \gamma, c)\,\tilde{\beta}_i' v_{it} + \varphi_i f_t + \varepsilon_{it} \tag{17}$$

In order to remove the factor f_t from Eq. (17), we first take the averages of the above equation and obtain f_t appropriately:

$$\overline{y}_t = \overline{\mu} + \overline{\beta}\,\overline{\delta}\left(\frac{\overline{x}_t - \overline{v}_t}{\overline{\delta}}\right) + \overline{F}(\cdot)\,\overline{\tilde{\beta}}_i'\,\overline{\delta}\left(\frac{\overline{x}_t - \overline{v}_t}{\overline{\delta}}\right) + \overline{\beta}\,\overline{v}_t + \overline{F}(\cdot)\,\overline{\tilde{\beta}}\,\overline{v}_t + \overline{\varphi}f_t + \overline{\varepsilon}_t \tag{18}$$

then, with some algebra, $\overline{y}_t$ can be written as:

$$\overline{y}_t = \overline{\mu} + \overline{\beta}\,\overline{x}_t + \overline{F}(\cdot)\,\overline{\tilde{\beta}}_i'\,\overline{x}_t + \overline{\varphi}f_t + \overline{\varepsilon}_t \tag{19}$$

Hence f_t is:

$$f_t = \frac{1}{\overline{\varphi}}\left(\overline{y}_t - \overline{\mu} - \overline{\beta}'\,\overline{x}_t - \overline{F}(\cdot)\,\overline{\tilde{\beta}}_i'\,\overline{x}_t - \overline{\varepsilon}_t\right) \tag{20}$$

we obtain f_t from Eq. (20) and substitute it in Eq. (15):

$$y_{it} = \mu_i + \beta_i' x_{it} + F(\cdot)\,\tilde{\beta}_i' x_{it} + \frac{\varphi_i}{\overline{\varphi}}\left[\overline{y}_t - \overline{\alpha} - \overline{\beta}\,\overline{x}_t - \overline{F}(\cdot)\,\overline{\tilde{\beta}}_i'\,\overline{x}_t - \overline{\varepsilon}_t\right] \tag{21}$$

again with relevant algebra, we obtain the auxiliary regression:

$$y_{it} = \tilde{\mu}_i + \beta_i' x_{it} + F(\cdot)\,\tilde{\beta}_i' x_{it} + a_i\overline{y}_t + b_i\overline{x}_t + \overline{F}(\cdot)c_i\,\overline{x}_t + \eta_{it} \tag{21}$$

where $\tilde{\mu}_i = \tilde{\mu}_i - \frac{\varphi_i}{\overline{\varphi}}\overline{\mu}$, $b_i = \frac{\varphi_i\,\overline{\beta}}{\overline{\varphi}}$, $a_i = \frac{\varphi_i}{\overline{\varphi}}$, $c_i = \frac{\varphi_i\,\overline{\tilde{\beta}}}{\overline{\varphi}}$, and $\eta_{it} = \varepsilon_{it} - \frac{\varphi_i}{\overline{\varphi}}\,\overline{\varepsilon}_t$

Now we can estimate the models by this transformation in order to eliminate the cross-section dependency.[20]

In order to remove the cross-section dependency from the PSTR estimates, we use Pesaran's (2006) CCE estimator and SURE-GLS. In Table 8, we report the results of these estimations along with the original estimates. We observe that the estimated parameters are similar to the parameters reported in Table 5. More accurately, we observe that the individual inflation estimates and the threshold values derived from these PSTR estimates corrected for cross-section dependency are reasonably close to the estimated individual inflation estimates and the threshold values based on non-remedied PSTR model which we put as original estimates in Table 8. Our primary PSTR results seem therefore to offset the occurrence of cross-section dependency but not fully. This

[20] This method can be used for the unit root test in order to eliminate cross-section dependency. Instead of Eq. 14 where we use bootstrap technique to eliminate cross-section dependecy, one can use the derived auxiliary regression by Pesaran (2006) technique. The auxiliary regression is as follows $\Delta z = \alpha_i + \delta_i z_{it-1}^{3} + a_{li}\overline{\Delta z} + b_i\overline{z} + b_i z_{t-1}^{3}\varepsilon_{it}$ for removing cross-section dependency. Therefore, from this auxiliary regression the test statistics can be obtained by Monte Carlo simulations and used for panel unit root test. All derivations and RATS program are available upon request.

Table 8
Estimation results of two-regime PSTR models which remedy cross-section dependency.

	M1:original	M1:CCE	M1:S–G	M2:original	M2:CCE	M2:S–G
β_{π_t}	−0.150	0.895	0.271	0.140	0.542	−0.178
	(−0.528)	(0.261)	(1.141)	(0.997)	(1.516)	(−0.600)
β_{I_t}	0.418***	0.133	0.218	–	–	–
	(4.680)	(0.956)	(0.691)			
β_{O_t}	0.050	0.089**	−0.219	–	–	–
	(1.485)	(2.157)	(−1.114)			
$\tilde{\beta}_{\tilde{\pi}_t}$	−0.579*	−0.958**	−0.802***	−0.467***	−0.717***	−0.427***
	(−1.665)	(−2.306)	(−4.448)	(−4.370)	(2.423)	(−2.941)
$\tilde{\beta}_{\tilde{I}_t}$	0.043	0.420	0.093	–	–	–
	(0.802)	(1.226)	(0.356)			
$\tilde{\beta}_{\tilde{O}_t}$	−0.010	−0.342	−0.038***	–	–	
	(−0.239)	(−0.917)	(−3.414)			
γ	3.308	5.067*	3.062***	69.052	49.032	43.272
	(0.742)	(1.859)	(2.840)	(0.147)	(0.164)	(2.338)
c	2.518***	2.427***	3.181***	3.460***	3.251***	3.449***
	(4.371)	(8.289)	(42.547)	(26.107)	(21.033)	(118.956)
Misspecification test: cross-section dependency CD_{LM}^{NL}						
	0.494					1.581
	(0.620)					(0.113)

(*) 10% significance level, (**) 5% significance level, and (***) 1% significance level.
** The values in the parentheses are t statistics.
*** Common correlated effects (CCE) estimators and S–G: SURE-GLS.

Table 9
Summary of cross-section dependency tests.

	Linear panel estimation	Linearized panel estimation	Non-linear panel estimation	Non-linear panel; factor removement CCE estimation
	CD_{LM}^{L}	CD_{LM}^{TL}	CD_{LM}^{NL}	CD_{LM}^{NLF}
Model 1	9.873	9.338	8.317	0.494
	(0.000)	(0.000)	(0.000)	(0.620)
Model 2	10.737	9.349	8.950	1.581
	(0.000)	(0.000)	(0.000)	(0.113)

* Under the null hypothesis the CD statistics converge to a normal standard distribution. The values in the parentheses are p values.

result can be read as PSTR models limit the cross-section dependency bias. We can see the evidence in Table 9 below.

From the cross-section dependency test that we compute in each stage, we see that the cross-section dependency diminishes. From the diagnostic check of linear panel estimations, we obtain test statistics 9.873 and 10.737 for models 1 and 2, respectively. Both of these test statistics confirm the existence of cross-section dependency. In the identification process of PSTR, we compute the CD statistics from the linearity tests where we use π_{t-1} as a transition variable in Eq. (3). From these computations, we obtain test statistics 9.338 and 9.349. When compared to linear panel CD tests, these results verify significant decline in cross-section dependency, but it is not removed fully. From the diagnostic check of non-linear panel estimation, we obtain test statistics 8.317 and 8.950 for models 1 and 2, respectively. Both of these test statistics are smaller than the previous test statistics. The progress of the test statistics demonstrates that non-linear estimation removes some parts of the cross-section depency due to model misspecification. There can be alternative explanations, but the scope of this study does not cover this issue.[21] Finally from the last column, we see that when we use CCE estimator, cross-section dependency is fully removed from our PSTR estimations.

5. Concluding remark

This paper provides new evidence on the non-linear impact of inflation on long-term economic growth. Recent empirical growth literature consistently suggests a negative non-linear inflation–growth relationship. Moreover, many studies addressing this issue explain this non-linear relationship with the threshold effects. That is, below a specific threshold value, inflation is found to have a statistically insignificant small positive or negative effect on growth, whereas above it, the effect becomes negative and statistically significant.

The empirical results reported in this paper strongly support the non-linear relationship between inflation and growth by using linearity tests used for the specification of PSTR models. Hence, the non-linear inflation–growth relationship is structured by the help of PSTR modeling. Moreover, this model specification allows empirical researchers to determine the number of thresholds. In particular, one can test whether there is a single or two threshold levels. A key issue in model specification is the endogenous determination of the threshold values. PSTR model, as opposed to many other models in the existent literature, which only allows for exogenous determination, is capable of determining the threshold values endogenously. Endogenous determination of threshold levels leads the researcher to find the precise levels which in turn give great advantage in analyzing the true relationship between inflation and growth. Threshold level for inflation is settled around 2.52% for six of the industrialized countries.

Panel estimations are subject to some problems due to sample and variables features. The problems can be summarized as heterogeneity, endogeneity and cross-section dependency. Regarding our sample and variables in the study, our estimation contaminated with all of these problems. Heterogeneity problem is solved automatically by adapting a PSTR modeling approach. For the endogeneity problem, the PSTR model and the new method that we propose for cross-section dependency present some remedies. To remedy the cross-section dependency problem, first of all, we introduce a new diagnostic check for cross-section dependency which is generalized to non-linear context. Then, we propose a new method which remedies cross-section dependency from the non-linear PSTR model. Besides, the new method that we introduce in this study may reduce endogeneity bias as well. By applying these methods, i.e., CCE and SURE-GLS, we compute threshold values as 2.44%, and 3.18%, respectively. For selected industrialized countries, our results suggest inflation targets around 2%. This level of inflation is more or less clearly announced by many central banks, for instance European Central Bank and the Bank of England. In conclusion, policymakers in these economies can achieve high growth rates by reducing inflation level below this threshold level. This information gives very important signal for the policymakers to impose new policies to provide economic stabilization.

Further avenues for research include applying the very same methodology to a larger group of developing countries, as well as improving the misspecification tests to control for a possible endogeneity bias.

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[21] Instead of Pesaran's (2006) method, we examine some empirical methods to find factor which can remove cross-section dependency. For this purpose, we use CD test with grid search techniques in order to find relevant factor. From these computations, we found out that there can be common factors which can be used instead of CCE estimator. The results and the RATS program are available upon request.

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