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On the Interaction Between Economic Growth and Business Cycles

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Abstract

The present paper studies the interaction between short-run fluctuations and economic growth by presenting empirical evidence of the impact of business cycle fluctuations on the rate of growth consistent with a constant unemployment rate in 13 Latin American and 18 OECD countries during the period 1981-2011. The results of both parametric (OLS and a panel estimator that allows for parameter heterogeneity and cross section dependence) and non-parametric (a penalized regression spline estimator) econometric techniques show that this measure of potential output experiences positive (negative) changes in periods of high (low) growth in the majority of countries, and, hence, that business cycles fluctuations have statistically significant effects on potential output. However, in contrast to the sample of OECD countries, less than half of the sample of Latin American countries experience statistically significant changes of this measure of potential output in periods of low growth.

JEL Classification: E32,O40,O51,O54
Keywords: growth and cycles, potential rate of growth, rate of growth consistent with a constant unemployment rate.

1 Introduction

Post-war economics has devoted a significant amount of research to the study of the interaction between business or short-run cycles and potential or long-run economic growth. The present paper estimates the effects that business cycle fluctuations generate on the rate of growth consistent with a constant unemployment rate, which can be identified with a measure of potential output growth since it represents the sum of labour force and labour productivity growth.

The empirical setting is tested for a sample of 13 Latin American (henceforth LA) and 18 OECD countries during the period 1981-2011 using Ordinary Least Squares (henceforth

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OLS); panel estimators with general multifactor error structure that take into account parameter heterogeneity and cross section dependence; and a penalized regression spline (henceforth PRS) estimator that allows for time-varying effects. The results show that business cycles have significant effects on this measure of potential rate of growth since the rate of output growth consistent with a constant unemployment rate experiences upward (downward) changes in periods of high (low) growth in the majority of countries. Nevertheless, we also find important differences between LA and OECD countries since the potential rate of growth associated with the low growth regime was found to be statistically significant in only 5 out of 13 LA countries; whereas it was found to be statistically significant in the majority of OECD countries.

Besides this introduction, the rest of the paper comprises 6 sections. Section 2 reviews the theoretical and empirical literature on the interaction between business cycles and economic growth, focusing on some recent empirical findings. Section 3 presents the empirical strategy. The fourth section provides a description of the techniques employed in the present context. The key empirical findings are presented and discussed in section 5. Finally, the main conclusions and some potentially relevant areas of future research are presented in the final section.

2 Background and motivation

2.1 Theoretical literature

The standard view presented by most introductory and intermediate-level macroeconomics textbooks is that business cycles and economic growth exist as separate phenomena and, therefore, that stabilization policies have no impact on the growth performance of the economies. However, it is possible to find many different economic theories that permit different types of long-run non-neutrality at the theoretical level.[1] Two well-known examples are non-superneutrality type models (57, 73) and fiscal policy models that allow for long-run effects (9). The former show that short-run monetary factors and portfolio decisions modify the capital stock, output per worker, and the interest rate in the steady state (73); and that a permanent increase in the rate of growth of money raises or lowers long-run output growth —depending on certain structural characteristics of the economy (57). In the same vein, Baxter and King (9) show that increases in government spending crowd-out or crowd-in investment in the long-run, which in turn influences the stock of capital and therefore the long-run aggregate supply.

On the other hand, models following the learning-by-doing approach (5, 11, 19, 53, 67, 68) highlight the pro-cyclical movements of both embodied and disembodied technical change, productivity growth, research and development, and the efficiency and intensity of resource utilization. This literature presents models with endogenous technology where a supply-side shock —such as a temporary rise in productivity, or a demand-side shock —such as an unanticipated rise in aggregate demand— can induce a permanent upward shift in the aggregate production function. One of the first models in this tradition is Stadler (67), who showed that if technology is endogenous, changes in aggregate demand can result in permanent changes in productivity, employment and output. More recent contributions have incorporated financial constraints (68); nominal rigidities and wage

[1] See also Keating (49) for more references on the theoretical literature linking long-run effects of aggregate demand on output.

contracts (11); uncertainty at the aggregate level (53); dynamic externalities (5); and endogenous diffusion of technologies (19).

Growth and fluctuations have also been studied by models in the Schumpeterian tradition. As mentioned by Christopoulos and León-Ledesma (17), within this approach it is possible to distinguish between the opportunity cost or intertemporal substitution models and the cleansing effect argument. The intertemporal substitution approach (2, 39, 66) stresses that investment on productivity-improving activities and normal production activities are substitutes rather than complements, and, thus, that productivity-improving activities can be carried out at the expense of productive activities. Therefore, these models consider that productivity may be counter-cyclical or pro-cyclical, depending on whether productivity improving activities have a disruptive effect on production or if they can be bought in the market without affecting current production (2). Recently, Nuño (56) has introduced a calibrated dynamic stochastic general equilibrium model with Schumpeterian endogenous growth that is capable of explaining the observed procyclicality of research and development.

The cleansing effect literature (14, 15, 21) considers that general profitability falls during recessions, so that business cycles "clean" the economy from inefficient units by taking older and less productive firms out of business, thus increasing average productivity. However, the impact of recessions on exit (and therefore on average productivity) depends on the entry rate of new firms. The "insulating" effect considers that the entry rate falls in recessions, so that old firms do not face the full reduction in demand and therefore the impact of the recession on the exit of the units is reduced. The theoretical and empirical results presented by Caballero and Hammour (15) show that cumulatively, recessions result in reduced rather than increased restructuring, and that this is likely to be socially costly once inefficiencies on both the creation and destruction margins are considered.

Finally, there is also a variety of models explicitly linking endogenous short-run fluctuations and endogenous long-run growth in a unified setting. Hence, long-run growth fluctuates endogenously and the economy can move back and forth between low and high growth periods. One such pioneering model is the rational expectations model by Evans et al. (26) in which the economy switches stochastically between periods of low and high growth. The expectational indeterminacy that is present in this model is induced by monopolistic competition and complementarity between different types of capital goods, regardless of the existence of externalities or increasing returns to scale. Francois and Shi (32) also include innovation cycles as an underlying cause of long-run growth, so that multiple stationary equilibria with different cycle lengths appear, and the growth rate is non-monotonically related to the length of the cycle. Some other examples within this stream of literature include quality-ladder growth models (33), portfolio approach models (55, 74), models with gradual diffusion of innovation (36), and models with distortionary taxes (65) and research and development subsidies (37).

2.2 Empirical literature

The links between short-run fluctuations and long-term growth have also been explored at the empirical level. We do not aim to review this literature at length and we will only provide some recent references.

In the first place, the estimation results presented by Kandil (48) show that: 1) adjustments on the supply-side are asymmetric in the face of positive and negative demand shocks; 2) the aggregate supply curve appears steeper in the face of both positive and negative demand shocks in less developed countries compared to more developed countries; and 3) the aggregate supply curve also appears steeper in the face of positive demand shocks compared to negative shocks for many countries. The asymmetric adjustment on the supply side is related to the notion of "persistence" of aggregate demand fluctuations explored in Fatás (27; 28; 29). His results show a strong positive correlation between the persistence of short-term fluctuations and long-term growth rates via the effects that business cycles have on aggregate demand, profits and technological progress. More recently, Fatás and Mihov (30) interpret fluctuations as a succession of three distinct phases (expansions, recessions and recoveries), which allows them to estimate that the cost of recessions and recoveries in the post-war United States (henceforth US) economy is approximately 20% of the peak GDP level; and that the recovery phase is as costly as the recession phase for earlier cycles. However, for the 1990 and 2007 cycles the recovery phase is much more costly than the recession phase given how weak growth is after the economy has passed the trough.

Different empirical studies have also emphasized the important quantitative connections between business cycles and economic growth using different approaches and techniques. Pedersen and Elmer (60) compared dates of business cycle turning points with dates of estimated trend breaks for 16 OECD countries, finding evidence of deterministic shifting and/or segmented time trends for all countries, and that more than 82% of the estimated trend breaks occur near a turning point. The quantile autoregression unit root test employed by Hosseinkouchack and Wolters (46) show that the effects of shocks on the US GDP have permanent persistent negative effects —specially the large recessionary ones; whereas the estimations of univariate and multivariate trend-cycle decomposition models of GDP by Guérin et al. (38) show evidence of regime changes in the growth of potential output for a few recession periods around 1974 and 2008 in the euro area.

In recent times, the empirical literature has also tried to identify the consequences of recessions on the different components of long-run growth. DeLong and Summers (23) have calculated that the financial crisis that began in 2007 brought about a sharp fall in fixed investment in the American economy —especially in residential construction— from its trend average level of 16.5% of potential output to a post-2008 average of 12.5%, for a cumulative shortfall (to 2012) of 14% point-years.[2] Similarly, Fernald (31) found that during the present recession and recovery itself potential output in the American economy has run well below its anaemic mid-2000s trend, reflecting especially the effect of weak investment on growth in capital input. The results of the stochastic production frontier analysis presented by Christopoulos and León-Ledesma (17) also show that recessions have significant negative effects on total factor productivity (henceforth TFP) from the last year of a recession up to 4 years after for a panel of 70 countries during the period of 1960-2000.

Finally, it is also possible to find various studies with special reference to the the medium- and long-run effects on output of financial crisis. Regarding the medium-term dynamics of output following banking crisis, Abiad et al. (1) consider a sample of 88 banking crisis over the past four decades and across countries with high, middle, and low income levels. The evidence shows that the path of output tends to be substantially and persistently depressed, with no rebound on average to the pre-crisis trend over the medium-run. They also find that the output loss in the short-run is mainly accounted for by TFP; and that, in the medium-run, the level of TFP recovers somewhat to its precrisis trend —unlike the employment rate and the capital-labour ratio.

With respect to the long-run effects of financial crisis on output, Boyd et al. (13) calculate that a sample of 23 countries countries experienced reductions in current and future output

[2] This shortfall is a consequence of the financial stringency of the crisis and of the rational decision of the firms that avoid building out its capacity rapidly because it already possesses substantial slack.

whose discounted present value is bounded between 63% and 302% of real GDP in the final pre-crisis year; and that only four out of 23 sample countries re-attain their pre-crisis trend level of output within 17 years of a crisis onset. Cerra and Saxena (16) calculate that the output loss ranges from around 1% to 16% for the various shocks studied in a large panel data set of 190 countries and, via impulse-response analysis, they show that less than 1% of the deepest output loss is regained by the end of ten years following a banking crisis. Papell and Prodan (59) develop a statistical methodology in order to identify and analyse slumps, finding that, amongst advanced countries, the return to potential GDP following recessions associated with financial crisis (9 years) is much longer than the return following other post-war recessions prior to 2007 (1.5 years). They also find that the magnitude of the recessions following financial crisis for emerging markets is larger than for advanced economies, and that its duration is comparable with recessions not associated with financial crisis in advanced economies.

Similar conclusions have been obtained by studies considering only OECD countries: using a univariate autoregressive growth equation on an unbalanced panel of 30 countries from 1960 to 2008, Furceri and Mourougane (35) calculate that financial crisis lower potential output by around 1.5-2.4% on average —with most of the impact coming from the effect on capital; whereas Bijapur (10) concludes that inflationary pressures tend to be stronger in the aftermath of financial crisis compared to non-crisis economic downturns, indicating impairment in productive potential.

Thus, the picture arising from this review shows a whole host of mechanisms —explored both at the theoretical and empirical levels— linking short-run or business cycles and trend or long-run or potential economic growth. These factors play a role in resource reallocation, industrial and firm-level restructuring, innovation, learning-by-doing, investment, and credit constraints faced by firms.

3 Empirical strategy

Different studies (47, 50, 52, 71, 72) have used the first difference version of Okun's law as a statistical device for estimating the rate of output growth (henceforth g_t) consistent with a stable unemployment rate. It can be assumed that, when the rate of unemployment (henceforth u_t) is constant —that is to say, when $\Delta u_t = 0$; where Δu_t is the change in the percentage level of unemployment rate, then output is growing at its potential or "natural" rate (henceforth g_n)[3] since this estimate represents the minimum level of output growth needed to reduce u_t given labour force and labour productivity growth.

As emphasized by Barreto and Howland (6), the research question determines the direction of regression. Thus, the best predictor of this measure of g_n can be found by regressing g_t on Δu_t[4]:

$$g_t = \alpha - \beta(\Delta u_t) + \varepsilon_1 \tag{1}$$

where in equation (1) β represents the Okun coefficient on unemployment and ε_1 depicts the

[3]To the best of our knowledge, Thirlwall (72) was the first to identify the rate of growth that keeps the unemployment rate constant with a measure of potential or "natural" output growth. The term "natural" stems from Roy Harrod's theoretical studies on the business cycle (41, 42, 43). Harrod defined the g_n as the "the maximum rate of growth allowed by the increase of population, accumulation of capital, technological improvement and the work leisure preference schedule, supposing that there is always full employment in some sense" (41: 30). Hence, in Harrod's view, g_n represents the "economic optimum growth rate" (43: 737), or the "welfare optimum in which resources are fully employed and the best available technology used." (42: 279)

[4]Thirlwall (72) also suggested reversing the dependent and independent variables in the traditional Okun's law specification in order to avoid estimation biases caused by labour hoarding.

stochastic disturbance term that satisfies the standard statistical properties. Hence, the estimate of g_n can be found when $\Delta u_t = 0$, so that $g_n = \alpha$.[5]

However, there is substantial empirical evidence that shows the presence of an asymmetric behaviour between output and unemployment. We have also taken into account the possibility that Okun's coefficient for different time points might be dissimilar, thus incorporating time-varying features in equation (1):

$$g_t = \alpha^* - \beta_t(\Delta u_t) + \varepsilon_2 \tag{2}$$

where in equation (2) the effect of Δu_t on g_t on time (henceforth t) is represented by the time-varying coefficient β_t. In the same vein, the estimated g_n obtained from equation (2) is α^*, which can be considered an estimate of the potential rate of growth that takes into account the possibility of a time-varying Okun coefficient on unemployment.

In order to study the interaction between the estimated g_n and g_t we follow the econometric specifications proposed by León-Ledesma and Thirlwall (52) and Lanzafame (51). Regarding the linear model depicted in equation (1), two dummy variables —both intercept and slope— that identify boom periods in each economy are introduced as follows:

$$g_t = \alpha_0 + \alpha_1(D) - \beta_0(\Delta u_t) + \beta_1(D * \Delta u_t) + \varepsilon_3 \tag{3}$$

where in equation (3) we have that D is the dummy variable that adopts the value of 1 ($D = 1$) in periods of growth buoyancy and zero otherwise; and $D * \Delta u_t$ is the slope dummy on Δu_t, so that the coefficient β_1 tries to capture the possible presence of an asymmetric Okun coefficient over the business cycle.

Likewise, the time-varying model depicted in equation (2) is re-estimated after the introduction of the respective D:

$$g_t = \alpha_0^* + \alpha_1^*(D) - \beta_t^1(\Delta u_t) + \varepsilon_4 \tag{4}$$

From equations (3) and (4) it is possible to identify two different g_ns associated with two different growth regimes. One g_n corresponds to the high growth regime (henceforth g_n^H), defined by the sum of the intercept term plus the coefficient on the dummy: $\alpha_0 + \alpha_1$ in equation (3) and $\alpha_0^* + \alpha_1^*$ in equation (4); whereas another g_n corresponds the low growth regime (henceforth g_n^L), defined by the intercept term: α_0 in equation (3) and α_1 in equation (4). Hence, if the respective coefficient estimates are found to be statistically significantly higher or lower (depending on each case) than the original estimate of g_n, then it is possible to say that the estimated g_n experienced changes during the expansion and contraction periods as a consequence of its interaction with g_t. In this sense, the difference between g_n^H and g_n ($g_n^H - g_n$) can be considered a measure of the output gap in high growth periods; whereas the difference between g_n^L and g_n ($g_n^L - g_n$) can be regarded as a measure of the output gap in low growth periods.

The periods of growth buoyancy used to construct the dummy variables have been identified following two different procedures that try to show the robustness of the results:

[5] Knotek (50) and IMF (47) have used a dynamic version of Okun's law in order to study the phenomenon of "jobless recoveries" —that is, periods following the end of recessions when output growth resumes but employment does not grow. We also estimated a dynamic version of Okun's law assuming that g_t can be affected by past values (up to two) of g_t and Δu_t. This initial general model was subsequently reduced in complexity by eliminating statistically non-significant variables according to the general-to-specific modelling approach. However, we do not report these results since the main conclusions remained unaltered (results are available on request). More importantly, the use of lags of the dependent variable (g_t) in equation (1) introduces further complications in a time-series setting since these variables are only weakly exogenous, and therefore its inclusion violates the exogeneity assumption of the OLS estimator (see also section 5.2.1).

1. When $g_t > g_n$.
2. When $g_t^{3-MA} > \bar{g}_t$; where g_t^{3-MA} represents a 3 year moving-average of g_t, and $\bar{g}_t$ is the average g_t during the period of study.

The second method has been used to identify expansion periods independently of the original estimation of g_n.

Equations (1) and (3) have been estimated using OLS and panel estimators with general multifactor error structures that take into account parameter heterogeneity and cross-section dependence (see Section 4.1 for the description); whereas equations (2) and (4) were estimated via the PRS estimator described in section 4.2.

In the estimation of equations (2) and (4) we have employed bootstrapped standard errors (2000 replications in all cases) in order to deal with the issue of second stage regressions with generated regressors (58); however, it was not possible to use bootstrapped standard errors when equation (4) was estimated using the panel data estimators due to insufficient number of observations.

Finally, the following misspecification tests were performed in the estimation results of equations (1) to (4) obtained via OLS and the PRS estimator: Breusch-Godfrey LM test for autocorrelation; Breusch-Pagan test for heteroskedasticity; Jarque-Bera normality test; and Ramsey RESET test for incorrect functional form. The relevant results of these diagnostic tests are discussed in each section.[6]

4 Econometric techniques

4.1 Panel estimators with general multifactor error structures

All mean group-type estimators follow the same basic methodology, namely they estimate N-group specific OLS regressions and then average the estimated coefficients across groups. For simplicity let us consider only the estimation of equation (2). Following Eberhardt (24), it is possible to offer a description of the mean group panel time-series estimators that allow for heterogeneous slope coefficients across group members:

$$g_{it} = \alpha_i - \beta_i(\Delta u_{it}) + z_{it} \tag{5}$$

$$z_{it} = \mu_i(f_t) + e^1_{it} \tag{6}$$

where in the equations above we have that, in addition to the previously defined variables, $i = 1, 2, ..., N$ indicates the cross-section (groups); $t = 1, 2, ..., T$ the time periods; z_{it} depicts the error term that has been specified in order to allow for cross-sectional correlation; f_t represents the unobserved common factors with heterogeneous factor loadings μ_i —which in turn can capture time-variant heterogeneity and cross-section dependence (henceforth CD); and e^1_{it} is an error component.

In the first place, the Mean Group (henceforth MG) estimator (61) can be regarded as a fully heterogeneous-coefficient model since it imposes no cross-group parameter restrictions.[7]

[6]The complete set of results is not reported but is available on request.

[7]Between the pooled and the MG estimator it is possible to find the Pooled Mean Group (PMG) estimator developed by Pesaran et al. (62). This approach combines both pooling and averaging since it constrains long-run coefficients to be identical but allows short-run coefficients, the intercept, and error variances to differ across groups. When this hypothesis is correct, the PMG estimator turns out to be more efficient than the MG estimator. The PMG estimator was not performed since no long-run slope coefficient were included.

However, the MG estimator does not pay attention to CD and assumes away $\mu_i(f_t)$ —or at best models these unobservable components with a linear trend; and, therefore, the results obtained via this approach will be inconsistent and biased if CD is present in the data.

There are several available tests of CD that have been developed, and most of them are typically based on the sample estimates of the pair-wise error correlations (henceforth $\widehat{\rho}_{ij}$).[8] We have employed Pesaran (63)'s CD test, which for the case of balanced panels is specified as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \widehat{\rho}_{ij} \right) \tag{7}$$

On the other hand, Pesaran (64)'s Common Correlated Effects Mean Group (henceforth CCEMG) estimator allows for CD and time-variant unobservables with heterogeneous impact across panel members. Assuming that the slope coefficients and regressors are uncorrelated, substituting for z_{it} and averaging equation (5) across i we have that:

$$f_t = \frac{1}{\bar{\mu}} \left[\bar{g}_t - \bar{\alpha} - \bar{\beta}(\overline{\Delta u_t}) - \bar{e}_t^1 \right] \tag{8}$$

where: $\bar{\mu} = \frac{1}{N}\sum_{i=1}^{N} \mu_i$; $\bar{g}_t = \frac{1}{N}\sum_{i=1}^{N} g_{it}$; $\bar{\alpha} = \frac{1}{N}\sum_{i=1}^{N} \alpha_i$; $\bar{\beta} = \frac{1}{N}\sum_{i=1}^{N} \beta_i$; $\overline{\Delta u_t} = \frac{1}{N}\sum_{i=1}^{N} \Delta u_{it}$; and $\bar{e}_t^1 = \frac{1}{N}\sum_{i=1}^{N} e_{it}^1$. For $N \to \infty$ and $\bar{\mu} \neq 0$, $\bar{e}_t^1 = 0$ and CD can be controlled using a linear combination of the cross-sectional averages of both g_{it} and Δu_{it}, that is, $\bar{g}_t$ and $\overline{\Delta u_t}$. Modifying equation (5) accordingly we have:

$$g_{it} = \alpha_i - \beta_i(\Delta u_{it}) + d_{1i}(\bar{g}_t) + d_{2i}(\overline{\Delta u_t}) + e_{it}^1 \tag{9}$$

Thus, in the present context the CCEMG estimator augments the group-specific regression equation including, besides Δu_{it}, both $\bar{g}_t$ and $\overline{\Delta u_t}$ as additional regressors; and the model parameters are estimated as simple averages of the country-specific estimates: $\widehat{\beta}_{CCEMG} = \frac{1}{N}\sum_{i=1}^{N} \beta_i$. However, as mentioned by Eberhardt (24), in empirical application the estimated coefficients on the cross-section-averaged variables and their average estimates are not interpretable in a meaningful way since they exist only to correct for the bias caused by the unobservable common factor. [9]

Eberhardt (24), Bond and Eberhardt (12), and Eberhardt and Teal (25) have recently developed an alternative method to the CCEMG with production function estimation in mind: the Augmented Mean Group (henceforth AMG) estimator.[10] The latter accounts for CD by including a "common dynamic process" (henceforth CDP) in the country regression, which represents an estimated cross-group average of the evolution of f_t over t and, in the context of cross-country growth models, it can be interpreted as common TFP evolution over time, whereby "common" is defined either in the literal sense or as the sample mean country-specific

[8] An early test of this type is the Breusch-Pagan LM test, which is based on the squares of $\widehat{\rho}_{ij}$ and tests the null hypothesis that $\widehat{\rho}_{ij}$ $\forall i \neq j$. However, the latter test tends to exhibit substantial size distortions in the case of panels with relative large N (18, 63).

[9] Pesaran (64) also developed the common correlated effects pooled (henceforth CCEP) estimator. The latter can be considered a generalization of the Fixed Effects estimator that allows for the possibility of error CD. Compared to the CCEMG, the CCEP is a more efficient estimator in small samples and assumes, possibly incorrectly, that the individual slope coefficients are the same across N —although the Monte Carlo simulations presented by Pesaran (64) show that this assumption does not affect its performance.

[10] The Monte Carlo simulations reported by Bond and Eberhardt (12) show that the AMG and CCEMG performed similarly well in terms of bias or root mean squared error in panels with nonstationary variables (cointegrated or not) and CD.

total factor productivity evolution. Nevertheless, the AMG estimator was developed controlling both for capital and for labour force growth. Since the intercept in equation (2) represents the rates of growth of labour productivity and labour force, the CDP in our estimations contains the elements that play a role in the rate of growth of capital productivity.

The AMG estimator is implemented in two steps in the context of equation (5):

$$\Delta g_{it} = -\beta_i^*(\Delta(\Delta u_{it})) + \sum_{t=2}^{T} c_t(\Delta D_t) + e_{it}^* \tag{10}$$

$$\Rightarrow \widehat{c_t} \equiv \widehat{\theta}_t$$

$$g_{it} = \alpha_i - \beta_i(\Delta u_{it}) + d_i(\widehat{\theta}_t) + e_{it}^1 \tag{11}$$

$$g_{it} - \widehat{\theta}_t = \alpha_i^1 - \beta_i^1(\Delta u_{it}) + e_{it}^2 \tag{12}$$

where in the equations above we have that c_t are the coefficients on the $T-1$ year dummies D_t in first differences, so that c_t represents the estimated CDP; and e_{it}^1 and e_{it}^2 are error terms.

Hence, in the first stage —equation (10), a pooled OLS regression of equation (5) in first differences augmented with D_t is estimated and the coefficients on the (differenced) year dummies are collected. These estimated coefficients ($\widehat{c_t}$) are then relabelled as $\widehat{\theta}_t$.[11] In the second stage —equations (11) and (12), the group-specific regression model is augmented with $\widehat{\theta}_t$. The latter can be done either including $\widehat{\theta}_t$ as an explicit variable as depicted in equation (11) or imposing the latter on each group member with unit coefficient by subtracting the estimated process from the dependent variable as depicted in equation (12). Finally, like in the MG and CCEMG estimators, the group-specific model parameters are then averaged across the panel, so that $\widehat{\beta}_{AMG} = \frac{1}{N}\sum_{i=1}^{N}\beta_i$.

In all the panel estimations presented in this paper we have employed the outlier-robust procedure developed by Hamilton (40) in order to attribute less weight to outliers.

4.2 Penalized regression spline representation

Equations (2) and (4) are time-varying coefficient models, that is, a special case of a varying-coefficient model (44) for which the effect modifier is t (77). We will only use equation (2) to illustrate the approach here adopted. We consider that the coefficient associated with Δu_t is an unknown smooth function (henceforth s) of t, with parameter vector δ —subject to centering constraints:

$$\beta_t = s(t,\delta) = \sum_{k=1}^{q} \delta_k b_k(t) \tag{13}$$

Therefore, under this approach, the vector of Δu_t effects, $\beta = (\beta_1, \ldots\ldots, \beta_T)_{TX1}$, is modelled as $s(t,\delta)$. The use of s is crucial since it allows for flexible specification of the dependence of the response of g_t on Δu_t; and models (2) and (4) can flexibly determine the functional shape of the relationship between g_t and Δu_t, thus avoiding some of the drawbacks of modelling data using parametric relationships.

[11] Bond and Eberhardt (12) and Eberhardt and Teal (25) explain that the c_t coefficients are extracted from the pooled regression in first differences since nonstationary variables and unobservable common factors are believed to bias the estimates in the pooled levels regressions. We have decided to perform the original AMG estimation notwithstanding we have a model in first differences since the sole interest is to analyse if the estimates of g_n^H and g_n^L differ from the original estimate of g_n.

The last part of equation (13) shows that s is represented using regression splines (54, 76). The regression spline of t is made up of a linear combination of known basis functions ($b_k(t)$) and unknown regression parameters (δ_k), where q is the number of basis functions.[12]

In order to ensure that the $b_k(t)$ have convenient mathematical properties and good numerical stability it is possible to use thin plate regression splines[13] with a penalized approach. The penalized approach here adopted keeps the number of q fixed at 10 since this ensures good flexibility in the estimation of the model and therefore controls the trade-off between the goodness of fit and roughness of s by the smoothing parameter (henceforth λ) (75).

Hence, equation (2) is fitted as follows:

$$\min \|\mathbf{g} - \mathbf{X}\delta\|^2 + \lambda \int \left\{ s^d(t,\delta) \right\}^2 \mathrm{d}t \tag{14}$$

Since regression splines are linear in their model parameters we have the following result (see Appendix B):

$$\min \|\mathbf{g} - \mathbf{X}\delta\|^2 + \lambda \delta^{\mathbf{T}} \mathbf{S} \delta, \text{ w.r.t. } \delta \tag{15}$$

where in equations (14) and (15) we have that $\mathbf{g}$ is the vector that contains the annual rates of growth; $\|.\|$ denotes the Euclidean norm; $\mathbf{X}$ is the model matrix containing $b_k(t)$ interacted with their corresponding Δu_t; δ denotes now the spline parameter vector; the integral measures the roughness of the smooth term to be used in the fitting process; d —which usually is set to 2 in order to study the possibility of nonlinearities— indicates the order of the derivative for the smooth term; and $\mathbf{S}$ is the known coefficient penalty matrix.

It turns out that the penalized least squares estimator of δ is:

$$\widehat{\delta} = \left(\mathbf{X}^{\mathbf{T}} \mathbf{X} + \lambda \mathbf{S} \right)^{-1} \mathbf{X}^{\mathbf{T}} \mathbf{g} \tag{16}$$

Wood (2006) has shown that the vector of smoothing parameters λ can be effectively estimated by minimization of a prediction error estimate such as the Generalized Cross Validation (henceforth **GCV**) score, so that:

$$\mathbf{GCV}(\lambda) = \frac{n\|\mathbf{g} - \widehat{\psi}\|^2}{\{n - \mathrm{tr}(\mathrm{A})\}^2} \tag{17}$$

where n in equation (17) denotes the number of observations and $\mathrm{tr}(\mathrm{A})$ represents the trace of the matrix A, which in turn represents the estimated degrees of freedom (henceforth edf) or number of parameters of the fitted model.

The vector λ enters the **GCV** score via:

$$\mathbf{A} = \mathbf{X} \left(\mathbf{X}^{\mathbf{T}} \mathbf{X} + \lambda \mathbf{S} \right)^{-1} \mathbf{X}^{\mathbf{T}} \tag{18}$$

$$\widehat{\psi} = \mathbf{A}\mathbf{g} \tag{19}$$

[12] A basis function is an element of a particular basis for a given function space. In other words, a basis function is an element of a set of linearly independent vectors that, in a linear combination, can represent every continuous function in a set of functions of a given kind.

[13] Thin plate regression splines are low rank isotropic smoothers since they approximate well the behaviour of a full rank thin plate spline. Its use possesses some specific advantages such as convenient mathematical properties, reasonably well computationally efficiency, and avoid the need to choose knot locations (54, 75, 76).

Therefore, once q and d have been set —usually $q = 10$ and $d = 2$ as was mentioned before, Wood's (2006) numerical procedure selects λ so that the part of smooth term complexity which has no support from the data will be suppressed. It is in this sense that this approach can produce smooth and reliable curve estimates.

On the other hand, if we are interested in testing smooth terms for equality to zero (for example, $\mathbf{H_o} : \beta_t$ in equation (2)), p-values calculations can be based on the following result:

$$\frac{\widehat{\delta}^{\mathbf{T}} \mathbf{V}_{\widehat{\delta}}^{\mathbf{r}-} \widehat{\delta}}{\widehat{\sigma}^2} \left[\frac{\sigma^2}{r} \right] = \frac{\widehat{\delta}^{\mathbf{T}} \mathbf{V}_{\widehat{\delta}}^{\mathbf{r}-} \widehat{\delta}}{r} \backsim F_{r,n-edf} \tag{20}$$

$$\mathbf{V}_{\widehat{\delta}} = \left(\mathbf{X^T X} + \mathbf{S}\right)^{-1} \mathbf{X^T X} \left(\mathbf{X^T X} + \mathbf{S}\right)^{-1} \sigma^2 \tag{21}$$

where in equations (20) and (21) $\widehat{\delta}$ contains the estimated coefficients for the smooth term; $\mathbf{V}_{\widehat{\delta}}$ is the covariance matrix of $\widehat{\delta}$ —which has to be employed in order to overcome possible matrix rank deficiencies due to the fact that the smoothing penalty may suppress some dimensions of the parameter space; and $\mathbf{V}_{\widehat{\delta}}^{\mathbf{r}-}$ is the rank r pseudo-inverse of $\mathbf{V}_{\widehat{\delta}}$.

In equation (20) the estimated variance (σ^2) can be calculated by the usual residual sum of squares divided by the residual degrees of freedom:

$$\widehat{\sigma}^2 = \frac{\|\mathbf{g} - \widehat{\psi}\|^2}{n - \mathrm{tr}(\mathrm{A})} \tag{22}$$

Finally, if the edf turn out to be statistically significant above 1 then is possible to say that the coefficients are statistically time-varying at the 5% level of significance.

5 Empirical results

5.1 Data description

We have used annual data for the period 1981-2011. We have employed this period of time due to the difficulty in finding long and consistent u_t time series for LA countries. The 13 LA countries included in the sample are: Argentina (Arg), Bolivia (Bol), Brazil (Bra), Chile (Chi), Colombia (Col), Costa Rica (CR), Ecuador (Ecu), Mexico (Mex), Nicaragua (Nic), Paraguay (Par), Peru (Peru), Uruguay (Uru), and Venezuela (Ven); whereas the 18 OECD sample countries are: Australia (Aus), Belgium (Bel), Canada (Can), Denmark (Den), Finland (Fin), France (Fra), Germany (Ger), Greece (Gre), Italy (Ita), Japan (Jap), Korea (Kor), Netherlands (Neth), Norway (Nor), Portugal (Por), Spain (Spa), Sweden (Swe), United Kingdom (UK), and the US.[14]

With respect to the sample of LA countries, GDP growth rates were extracted from the *World Bank electronic database*. On the other hand, it is challenging to find consistent u_t series. We have extracted the latter from the new dataset constructed by Ball et al. (4), which provides reasonably consistent u_t series within each country and therefore can be used to study the evolution of unemployment over time. Nevertheless, this dataset presents some missing observations that are necessary for the period of study, and therefore it was necessary to resort to

[14]Mex and Chi became OECD members respectively in 1994 and 2010. However, we have decided to include both countries in the LA sample.

the *Economic Commission for Latin American and the Caribbean (ECLAC) database* (Table A1 in the Appendix shows the details for each country).

Regarding the sample of OECD countries, all series were extracted from the *OECD electronic database*. Missing observations were extracted from the *International Monetary Fund (IMF)* data and statistics web page (see also Table A1 for the details of the u_t series).

In the Instrumental Variable (henceforth IV) estimations of equation (1) (see Section 5.2.1) we also employed different lags of the rates of growth of labour productivity (henceforth τ_t) and total labour force (henceforth l_t) as instruments. Labour productivity was measured as GDP per number of total hours worked. As for the LA countries, the number of total hours worked series were available only for Arg, Bra, Chi, Col, Mex, Peru, and Ven via *The Conference Board Total Economy Database of the Groningen Growth and Development Centre*. Labour productivity for the rest of LA countries was calculated as GDP per person employed, and these series were extracted from the *World Bank electronic database*. In turn, labour productivity series for the *OECD* countries were extracted from the *OECD* database.

Finally, labour force series for the LA countries were extracted from the *World Bank database*; whereas for the OECD we employed the *OECD electronic dataset* (although it was not possible to find labour force series for the cases Jap, Kor, and Swe).

5.2 Potential rates of growth estimates

5.2.1 OLS and IV

The results of the estimation of equation (1) via OLS are presented in Table 1, together with the respective Adjusted R^2 (henceforth Adj. R^2) values. We have employed the Cochrane-Orcutt transformation for the few countries that presented autocorrelation problems (Arg, Bol, Jap, Kor, Nor, and the UK); and the Huber-White-sandwich estimator for the variance-covariance matrix in those countries that presented heteroskedasticity problems (Aus, Den, Fin, and Ita). Normality problems were also found for the cases of CR, Nic and Ger. In all other cases the diagnostic tests were satisfied.

Nevertheless, the fact that both output and unemployment are endogenous variables to a complex system means that the crucial zero-conditional mean assumption required to implement the OLS estimator is not satisfied. We have dealt with the possible endogeneity bias using IV estimation as follows. For each individual country we re-estimated equation (1) using as instruments different combinations of the lags (up to two) of Δu_t, τ_t, and l_t.[15] We then performed a *C*-statistic —also known as "Generalized Method of Moments (GMM) distance" or "difference-in-Sargan" statistic— type test of endogeneity (45)[16], which can be considered as a test of the appropriateness of OLS and the necessity to resort to IV.[17]

The null hypothesis of the *C*-test of endogeneity (*i.e.*, Δu_t can be treated as an exogenous variable) was rejected for the majority of cases cases —with the exceptions of Bol, Col, CR,

[15] These estimations are not reported here in order to present only the relevant results, but are available from the author on request.

[16] Like the *C*- statistic, this endogeneity test is defined as the difference of two Sargan-Hansen statistics: one for the equation with the smaller set of instruments, where Δu_t is treated as endogenous, and one for the equation with the larger set of instruments, where Δu_t is treated as exogenous. Also like the *C*-statistic, the estimated covariance matrix used guarantees a non-negative test statistic (7, 8).

[17] Under conditional homoskedasticity, the *C*-statistic type test of endogeneity is numerically equal to a Hausman test statistic (45). Thus, like the Hausman test, this test of endogeneity is formed by choosing OLS as the efficient estimator and the IV estimator as the inefficient but consistent estimator (7, 8). However, unlike the traditional Durbin-Wu-Hausman tests, the *C*-statistic type test of endogeneity is robust to violations of conditional homoskedasticity.

Mex, Ven, Den, Ger, Gre, and Por— when the sets of instruments presented in Table 1 were used. These instruments seem to be uncorrelated with the error term (*i.e.*, no rejection of the null hypothesis) according to the tests of overidentifying restrictions: Hansen's J-statistic (consistent in the presence of heteroskedasticity and autocorrelation) and the Sargan test.[18] Hence, for these countries it is more appropriate to retrieve the estimates of g_n from the IV coefficient estimates instead of the OLS results.

However, with the exception of Fin, the IV estimation results obtained via Two-stage Least Squares (henceforth 2SLS) are subject to the problem of weak identification since it was not possible to reject the null hypothesis (*i.e.*, instruments are only marginally relevant) when the respective values obtained for the Cragg-Donald F-statistic were compared with the Stock and Yogo (70) weak identification critical values.[19] Moreover, the null hypothesis (*i.e.*, instruments are not correlated with the endogenous regressors) of the underidentification test —LM version of the Anderson (3) canonical correlations test— was rejected only for the cases of Arg, Uru, Bel, Can, Fin, Jap, Spa, Swe, UK, and the US. The latter also suggests that, for the rest of the countries, the instruments used may be inadequate to identify the equation.

Therefore, with the exception of Fin, we employed Fuller (34)'s modified limited-information maximum likelihood (LIML) estimator with $a = 1$ (where a is the Fuller parameter). The latter is more robust to weak instruments than 2SLS —when viewed from the perspective of bias— and Monte Carlo simulations report substantial reductions in bias and mean squared error using Fuller-k estimators relative to 2SLS and LIML (69).[20] These results satisfy the diagnostic tests according to the Cumby-Huizinga test for autocorrelation; Pagan-Hall heteroskedasticity test; Doornik–Hansen test of multivariate normality; and Ramsey/Pesaran-Taylor RESET test. Table 1 presents the results of the Fuller's LIML estimation and the Root Mean Square Error (henceforth RMSE) associated with these estimations.

5.2.2 Panel estimators with general multifactor error structures

We first implemented the standard MG estimator with and without country-specific time trends, which can be used to capture omitted idiosyncratic processes evolving in a linear fashion over time. The existence of 16 out of 31 significant country-specific time trends at the 10% level of significance may indicate the presence of common factors and therefore of CD. This is corroborated by the strong rejection of the null hypothesis of the CD tests: the CD associated with the MG estimation without country-specific time trends is 16.12; whereas the one for the MG estimation with country-specific time trends is 18.17 (p-value=0 in both cases).[21] Hence, a panel estimation of this type requires estimators robust to the presence of CD such as the CCEMG and the AMG estimators.

We then performed the CCEMG estimation as depicted in equation (9). However, the estimated g_ns turned out to be significant in only 9 out of 31 cases. The introduction of country-specific time trends did not change these results since in this case we only found 15 statistically

[18]Results available upon request.

[19]Note that, for the case of a single endogenous regressor, the Cragg-Donald F-statistic is simply the first-stage F-statistic (70). Indeed, as a rule of thumb, for the case of one endogenous regressor the first-stage F-statistic needs to exceed 10 for IV inference to be reliable (8, 69). The only country that satisfied this condition was Fin.

[20]The results obtained using other estimators such as the LIML and the Fuller estimator with $a = 4$ were fairly similar to the ones here reported.

[21]The null hypothesis was also strongly rejected when the CD test was applied to the individual g_t and Δu_t series. The value of the CD test associated with the g_t series was 31.43; whereas the one associated with the Δu_t series was 22.48 (p-value=0 in both cases).

significant estimates of g_n. The use of the CCEP estimator (using bootstrapped standard errors with 2000 replications) also showed that the intercept term for the panel was statistically non-significant. One possible explanation of why the estimated g_n turns out to be statistically non-significant when the CCE methodology was employed may be that the latter approach uses a high number of degrees of freedom since, in general, for q regressors it requires $q+1$ cross-sectional averages on the right-hand-side. Indeed, as Eberhardt (24) has mentioned, both the CCEMG and the AMG estimators have been designed for "moderate-T, moderate-N" macro panels. In our particular case we have a relatively short sample, and therefore a priori we can expect that the CCEMG and CCEP estimators generate fewer significant estimates compared to the AMG estimator.

In turn, the results of the AMG estimation including the CDP as an explicit regressor as depicted in equation (11) (henceforth AMG[1]) and imposing the CDP with unit coefficient as depicted in equation (12) (henceforth AMG[2]) can be found in Table 1. We also estimated both models including country-specific time trends, finding that these were statistically significant in 17 countries in the AMG[1] estimation and in 18 cases in the AMG[2] estimation. However, since the parameter estimates remained unaltered, we only have considered the results of the AMG estimation without country-specific time trends.

5.2.3 PRS

The results of the estimation of equation (2) are also reported in Table 1. Arg, Bol and the UK presented problems of autocorrelation. Therefore, for the first two countries we included one lag of g_t using an unknown smooth function as extra coefficient: $s(g_{t-1})$; whereas for the UK it was also necessary to include Δu_{t-1} as an extra regressor.[22] All other estimation results satisfied the diagnostic tests, although heteroskedasticity problems were present in Bol, Aus, and Swe; CR, Ger and the UK presented problems of normality; and Fin and Neth presented problems of correct functional form. In general, the estimations using the PRS approach seem to show higher Adj. R^2 values compared to the ones obtained via OLS estimation.

Figures 1 and 2 present the results of the time-varying Okun coefficients on unemployment. From Table 1 it is also possible to see that the edf of the smooth terms are statistically significant above 1 in all cases except for Bol, Chi, Ecu, Mex, Uru, Ven, Den, Ger, and Swe; which in turn means that the parameter β_t is statistically time-variant during the period of study in all countries except in these 9 cases.

A precise description of these empirical results need to be interpreted in the light of a mix of components —such as the economic growth of a country, its demographic structure, labour market flexibility, labour market policies, policy implementation timing, and spread of policies in each country. This exceeds the purpose of the current paper and is left for future research. However, it is necessary to emphasize that, with respect to the sample of OECD countries, the results here obtained corroborate those found by Zanin and Marra (77). For the period of 1961-2009, Zanin and Marra (77) regress Δu_t on g_t (the inverse relationship of equation (1)), finding time-varying Okun coefficients in their sample of 9 OECD countries (Aus, Fin, Fra, Gre, Ireland, Ita, Neth, Por, and Spa).[23] In the same vein, Daly et al. (20) have estimated equation (1) using quarterly data for the US economy. Their results show a reduction in the

[22] The edf of the smooth term estimates on g_{t-1} are above 1 in all cases (Arg=1.96; Bol=3.50; UK=1.41), and their respective p-values are statistically significant at the 5% level. The edf of the smooth term coefficient on Δu_{t-1} for the UK is 1 (p-value=0).

[23] Note that the time-varying coefficients obtained in our study represent Okun coefficients on unemployment; whereas the ones found by Zanin and Marra (77) represent time-varying Okun coefficients on output. Hence, strictly speaking, it is not possible to establish a direct comparison between the results.

Okun coefficient on unemployment for the period 1981-2011 (from around -1.7 to around -1.5) using rolling regressions (40 quarter rolling window). This is also obtained in our results using the PRS estimator since the Okun coefficient is reduced from -2.1 to -1.5.

[INSERT TABLE 1 ABOUT HERE]
[INSERT FIGURE 1 ABOUT HERE]
[INSERT FIGURE 2 ABOUT HERE]

5.2.4 Summary of results

The estimates of g_n obtained with the different techniques for all countries are summarized in Table 2. From the latter it is possible to observe that the results obtained are fairly similar. The AMG estimations (both AMG[1] and AMG[2]) show relative lower estimates of g_n compared to the ones obtained via OLS/IV and the PRS in the majority of countries (the only two exceptions are Can and the US when the AMG[1] estimation was performed).

[INSERT TABLE 2 ABOUT HERE]

5.3 Estimates of the potential rates of growth in low and high growth regimes

The results of the estimation of equations (3) and (4) using the different techniques are presented in Tables 3 and 4 below. The former presents the estimations using the first dummy variable described in Section 3 in order to identify expansion periods; whereas the latter presents the estimations using the second dummy variable. We only report the coefficient estimates on the intercepts and on the dummy variables, together with the respective Adj. R^2 values in order to facilitate the presentation of both Tables.[24]

The OLS and PRS estimation results did not present problems of autocorrelation in all cases. Regarding the OLS estimation results presented in Table 3, normality problems were found for the cases of CR, Nic, Par, Den, Fin, Ger, Ita, and Neth; and correct functional form problems were found in Col, Fin, Ita, and the US. On the other hand, when the PRS estimator was used, normality problems were found for the cases of CR, Nic, Aus, Bel, Ger, and the Neth; and correct functional form problems were found for the cases of Col, Aus, Den, Fin, and the UK. In all other cases the diagnostic tests were satisfied.

With respect to the estimations presented in Table 4, all countries satisfy the respective diagnostic tests, with the following exceptions: normality problems were found for the cases of CR, Nic, Fin, Ger, Ita, Neth when the OLS estimator was employed, and for the cases of CR, Nic, Ger, and Neth when the PRS estimation was used; correct functional form problems were found in Den and the US in the OLS estimation, and in the UK when the PRS estimator was used.

Finally, regarding the AMG panel estimation of equation (3), the first dummy variable introduced in this case corresponds to the estimate of g_n obtained for the panel as a whole (that is, 2.20); whereas the second dummy was built with respect to the average g_t of all countries (that is, 2.49).

[INSERT TABLE 3 ABOUT HERE]
[INSERT TABLE 4 ABOUT HERE]

[24]The complete estimation results are available upon request.

5.3.1 Summary of results

Using the results presented in Tables 3 and 4, Table 5 computes the estimates of g_n^L and g_n^H as described in section 3. This Table shows that the g_n^Hs and g_n^Ls obtained with the different econometric techniques are similar, so that we can be confident that the results obtained are robust. In general, all countries present statistically significant g_n^Hs; whereas not all countries present statistically significant g_n^Ls. The latter is particularly relevant for LA countries since the only countries that presented statistically significant g_n^Ls were Chi, Col, CR, Ecu, and Mex. Regarding the sample of OECD countries, Fin and Gre are the only two countries for which the respective g_n^Ls were found to be statistically non-significant in most of the estimations.

[INSERT TABLE 5 ABOUT HERE]

In turn, Table 6 calculates the simple difference between the different estimates of g_n (presented in Table 2) and the different estimates of g_n^L and g_n^H (presented in Table 5). As mentioned before, $g_n^L - g_n$ can be considered a measure of the output gap in low growth periods; whereas $g_n^H - g_n$ can be regarded as a measure of the output gap in high growth periods. The output gaps for the respective countries are similar in all cases and show the robustness of the results obtained.

In Table 6 we have also included two extra columns that present the average gaps both for low and high growth periods, which are shown in bold font. The latter were calculated only for those countries that presented statistically significant g_n^Ls or g_n^Hs in at least 4 out of the 8 estimations. This analysis shows that the countries that presented the highest average output gap in low growth periods (that is, the highest average measure of $g_n^L - g_n$) are CR, Kor, and Chi; whereas the countries with the lowest average output gap are Ita, Ger, and Spa. On the other hand, the countries that presented the highest measure of output gap in high growth periods (the highest average measure of $g_n^H - g_n$) were Arg, Peru, and Uru; whereas the lowest output gap is present in Fin, US, and Aus.

[INSERT TABLE 6 ABOUT HERE]

6 Concluding remarks

The present article is related to the different post-war empirical studies that have dealt with the interaction between short-run or business cycle fluctuations and long-run or potential economic growth. This paper has identified the rate of output growth consistent with a constant unemployment rate with a simple statistical measure of potential output and has estimated the effects that business cycles generate on it for a sample of 13 Latin American and 18 OECD countries during the period 1981-2011.

Using OLS estimation, a panel estimator that takes into account parameter heterogeneity and cross-section dependence, and a non-parametric specification estimated via penalized regression splines, we find evidence that business cycle fluctuations have significant effects on this measure of potential rate of growth in the majority of countries. The rate of output growth consistent with a constant unemployment rate experiences increments in periods of economic expansion; whereas it suffers decrements in periods of low growth. However, there are also important and interesting differences between countries in the sample since only less than half of the Latin American countries (5 out of 13 cases) presented statistically significant potential rates of growth associated with the low growth regime; whereas the latter were found to be significant in most of the OECD countries (16 out of 18 cases). This is particularly important in order to discuss the relevant stabilization policies required for each country.

Our results point out that the study of the interaction between business cycle fluctuations and economic growth requires the implementation of various models that can offer a more detailed description of the particular mechanisms that play a role in each specific country. Thus, a potentially fruitful line of research can be to try to identify what types of non-neutrality are relevant for each economy using, for example, long-run non-neutral Blanchard-Quah decompositions as in Keating (49) and trend-cycle decomposition models that incorporate the possibility of regime switches as in Guérin et al. (38). Micro level studies exploring the different mechanisms relating recessions and expansions and productivity are also particularly relevant in order to distinguish the impact of business cycles in terms of level and in terms of the long-term growth path. One possible way of doing the latter is to use stochastic frontier analysis as in Christopoulos and León-Ledesma (17).

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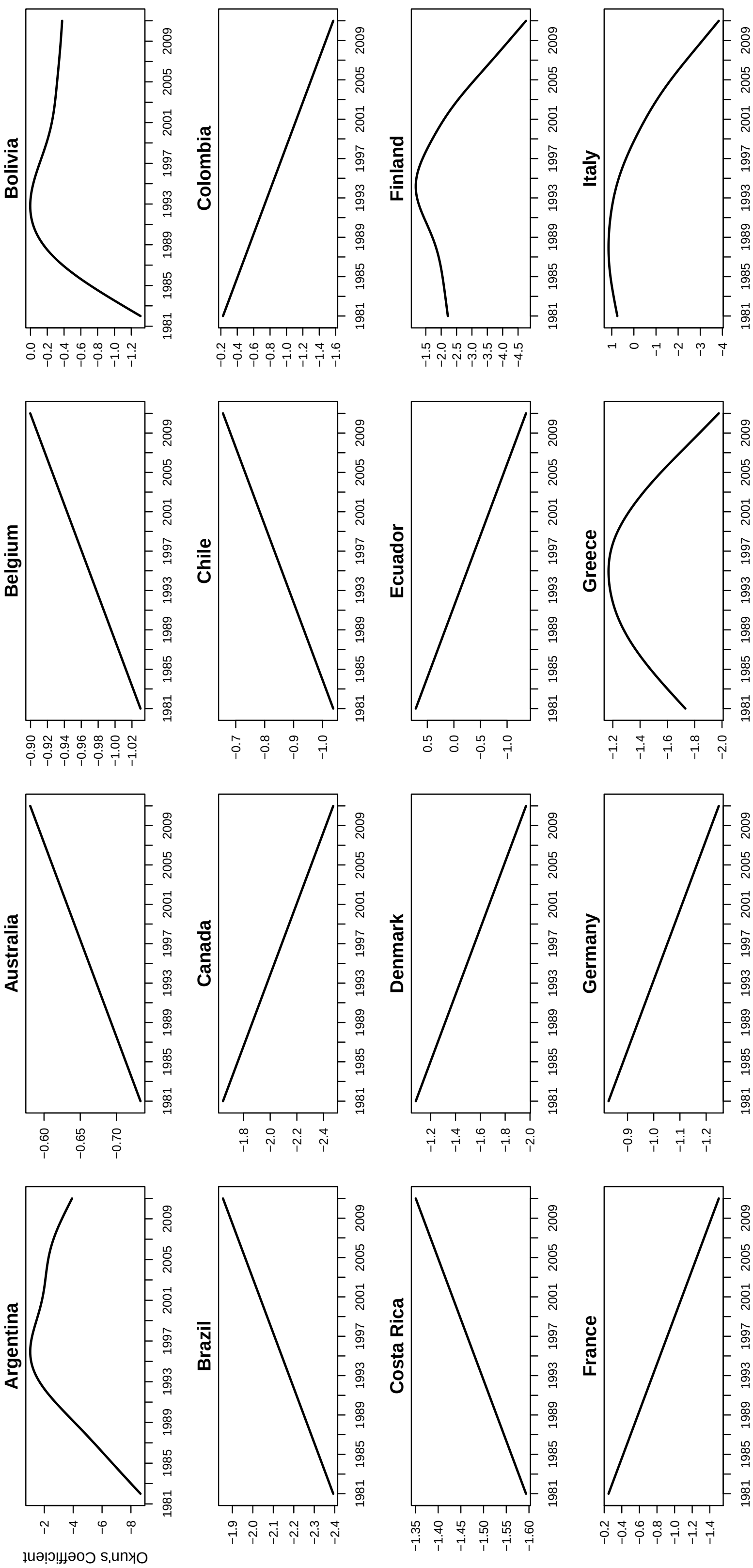

Figure 1. Time-varying Okun coefficients (first 16 countries)

Table 1. Estimates of equations (1) and (2)

	OLS[a]			IV[b]			AMG[1][c]			AMG[2][d]		PRS[e]		
	α	β	Adj. R^2	α	Instruments used[f]	RMSE	α	β	d	α	β	α^*	β_t[g]	Adj. R^2
LA														
Arg	3.686^	2.045**	0.55	3.081*	$\Delta u_{t-1},\tau_{t-1},l_{t-1}$	7.02	1.954*	1.542**	2.467**	2.595**	1.665**	3.057**	3.093*	0.70
Bol	2.996*	0.195^	0.04	-[h]	-[h]	-[h]	2.288**	0.344	0.803^	2.199**	0.309	2.748**	3.400	0.68
Bra	2.445**	2.170**	0.46	2.879**	$\Delta u_{t-1},\tau_{t-1}$	3.11	2.001**	1.958**	1.079**	2.034**	1.974**	2.460**	2.0**	0.44
Chi	4.709**	0.953**	0.55	4.814**	$\Delta u_{t-1},\tau_{t-1}$	5.01	4.048**	0.719**	1.604**	4.297**	0.807**	4.738**	1.0	0.54
Col	3.661**	0.937**	0.49	-[h]	-[h]	-[h]	3.393**	0.816**	0.590*	3.208**	0.731**	3.561**	2.0**	0.54
CR	4.181**	1.487**	0.29	-[h]	-[h]	-[h]	3.585**	0.905*	1.306*	3.724**	1.041**	4.176**	2.0**	0.26
Ecu	3.019**	0.348	0.02	3.005**	$\Delta u_{t-1},\tau_{t-1}$	4.25	2.658**	0.258	0.845	2.592**	0.242	2.841**	2.0	0.09
Mex	2.518**	2.604**	0.54	-[h]	-[h]	-[h]	2.135**	2.288**	0.883*	2.084**	2.246**	2.538**	1.074	0.54
Nic	1.883**	0.918*	0.17	2.047*	$\Delta u_{t-1},l_{t-1}$	4.89	1.655*	0.851*	0.522	1.447*	0.789*	1.895**	2.0*	0.14
Par	3.066**	1.315**	0.25	2.988**	$\Delta u_{t-1},\Delta u_{t-2}$	4.39	2.327**	0.935*	1.663**	2.621**	1.086**	2.684**	4.233**	0.44
Peru	3.175**	2.112**	0.24	3.032*	τ_{t-1},l_{t-1}	6.98	2.361*	1.809**	1.922*	2.751**	1.954**	3.117**	3.039**	0.37
Uru	2.125**	2.036**	0.50	1.931*	$\Delta u_{t-1},\Delta u_{t-2}$	4.23	1.426*	1.524**	1.770**	1.730**	1.747**	2.291**	1.0	0.49
Ven	2.449**	2.626**	0.64	-[h]	-[h]	-[h]	1.742**	2.299**	1.599**	2.007**	2.421**	2.144**	1.0	0.68
OECD														
Aus	3.223**	0.686	0.18	3.255**	$\Delta u_{t-1},\tau_{t-1}$	1.91	3.082**	0.516^	0.343	2.812**	0.189	3.232**	2.0^	0.12
Bel	1.846**	0.974**	0.34	1.952**	$\Delta u_{t-1},l_{t-1}$	1.47	1.528**	0.749**	0.764**	1.429**	0.679**	1.851**	2.0**	0.31
Can	2.552**	1.867**	0.76	2.558**	$\Delta u_{t-1},\Delta u_{t-2}$	1.23	2.613**	1.969**	-0.144	2.127**	1.149**	2.520**	2.0**	0.77
Den	1.774**	1.493**	0.62	-[h]	-[h]	-[h]	1.605**	1.282**	0.388	1.339**	0.949**	1.793**	1.0	0.63
Fin	2.507**	1.563**	0.59	2.446**	$\Delta u_{t-1},\Delta u_{t-2}$	2.31	2.039**	1.440**	1.067**	2.069**	1.448**	2.350**	2.364**	0.72
Fra	1.918**	0.888**	0.24	1.836**	$\Delta u_{t-1},\tau_{t-2}$	1.59	1.675**	0.816**	0.553**	1.479**	0.757**	1.834**	2.0**	0.26
Ger	1.901**	1.025**	0.19	-[h]	-[h]	-[h]	1.480**	0.750*	0.931**	1.448**	0.729*	1.859**	1.0	0.17
Gre	2.311**	1.809**	0.56	-[h]	-[h]	-[h]	2.182**	1.764**	0.252	1.797**	1.629**	2.282**	2.54**	0.56
Ita	1.443**	0.241	0.01	1.502**	$\Delta u_{t-2},\tau_{t-2},l_{t-2}$	2.71	1.012**	0.035	0.998**	1.011**	0.035	1.344**	3.02**	0.32
Jap	2.082*	4.702**	0.42	1.770*	$\Delta u_{t-1},\tau_{t-2}$	3.29	2.372**	4.059**	0.138	1.894**	2.686*	2.459**	2.162**	0.28
Kor	6.445**	3.117**	0.72	6.669**	$\Delta u_{t-1},\tau_{t-1},\tau_{t-2}$	3.87	6.361**	2.844**	0.515	6.155**	2.827**	6.340**	1.0^	0.52
Neth	2.213**	0.683**	0.22	2.176**	τ_{t-1},l_{t-1}	2.08	1.821**	0.369^	0.922**	1.788**	0.343^	2.209**	2.772**	0.34
Nor	2.573**	1.235*	0.21	2.759**	$\Delta u_{t-2},\tau_{t-1},l_{t-1}$	2.83	2.293**	0.994*	0.699**	2.151**	0.731^	2.659**	2.0**	0.26
Por	2.679**	2.409**	0.68	-[h]	-[h]	-[h]	2.459**	2.321**	0.477*	2.217**	2.224**	2.545**	2.0**	0.69
Spa	2.817**	0.847**	0.81	2.887**	$\Delta u_{t-1},l_{t-1},\tau_{t-2}$	1.01	2.744**	0.816**	0.147	2.319**	0.639**	3.129**	4.946**	0.87
Swe	2.462**	1.467**	0.48	2.347**	$\Delta u_{t-1},\Delta u_{t-2}$	2.09	2.003**	1.269**	0.991**	1.999**	1.267**	2.508**	1.907	0.50
UK	2.406**	1.624**	0.50	2.565**	$\Delta u_{t-1},l_{t-1}$	1.97	2.244**	1.207**	0.599*	2.065**	1.028**	2.534**	1.0^	0.70
US	2.892**	1.771**	0.78	2.931**	$\Delta u_{t-1},\Delta u_{t-2}$	1.05	2.989**	1.939**	-0.206	2.421**	0.955**	2.859**	2.0**	0.78

Notes: [a]The following countries presented autocorrelation problems: Arg, Bol, Jap, Kor, Nor, and the UK. In these countries we used the Cochrane-Orcutt transformation (together with the Huber-White-sandwich estimator). On the other hand, the following countries presented heteroskedasticity problems: Aus, Den, Fin, and Ita. In these countries we employed the Huber-White-sandwich estimator for the variance-covariance matrix; [b]With the exception of Fin, all results were obtained using 1 as the non-negative Fuller parameter. For the case of Fin we used the 2SLS estimator since the instruments used seem to be relevant according to the Cragg-Donald Wald F-statistic; [c]CDP included as additional regressor; [d]Imposing the CDP with unit coefficient; [e]The following countries presented autocorrelation problems: Arg, Bol, and the UK. For the cases of Arg and Bol we included g_{t-1} as extra regressor, whereas for the UK it was necessary to include both g_{t-1} and Δu_{t-1}; [f]Notation: τ_{t-i}=lags of the rate of growth of labour productivity; l_{t-i}=lags of the rate of growth of total labour force; Δu_{t-i}=lags of the change in the percentage level of unemployment rate; $i=1,2$; [g]The estimated degrees of freedom (edf) of the smooth terms are shown; [h]Not reported since the null hypothesis of the C-statistic type test of endogeneity was not rejected in these cases.

^,*, and ** respectively denote rejection of the null hypothesis at the 10%, 5%, and 1% confidence levels.

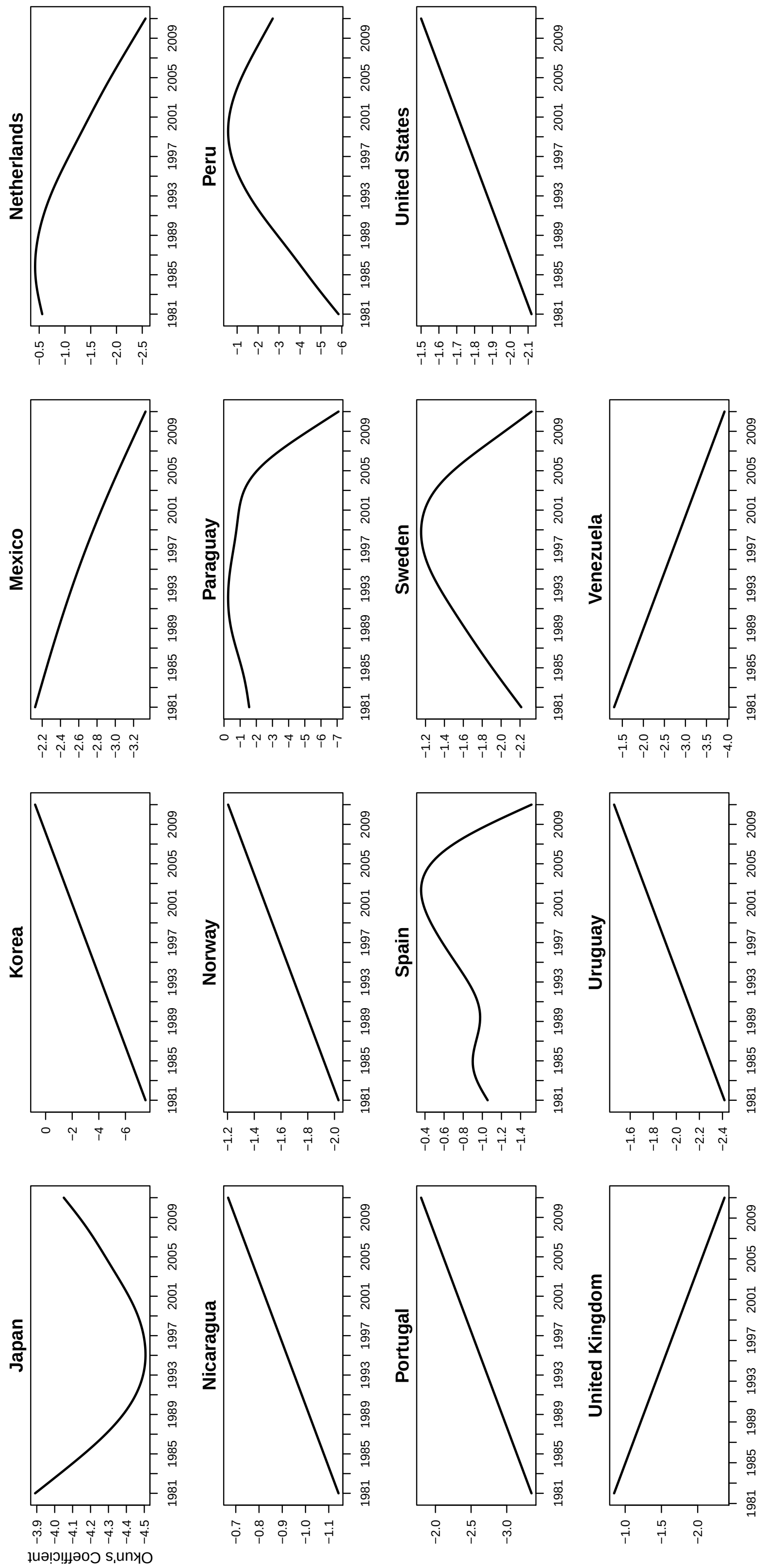

Figure 2. Time-varying Okun coefficients (last 15 countries)

Table 2. Potential rates of growth estimates

	OLS or IV[a]	AMG[1][b]	AMG[2][c]	PRS
LA				
Arg	3.08	1.95	2.60	3.06
Bol	3.00	2.29	2.20	2.75
Bra	2.88	2.00	2.03	2.46
Chi	4.81	4.05	4.30	4.74
Col	3.66	3.39	3.21	3.56
CR	4.18	3.59	3.72	4.18
Ecu	3.01	2.66	2.59	2.84
Mex	2.52	2.14	2.08	2.54
Nic	2.05	1.66	1.45	1.90
Par	2.99	2.33	2.62	2.68
Peru	3.03	2.36	2.75	3.12
Uru	1.93	1.43	1.73	2.29
Ven	2.45	1.74	2.01	2.14
OECD				
Aus	3.26	3.08	2.81	3.23
Bel	1.95	1.53	1.43	1.85
Can	2.56	2.61	2.13	2.52
Den	1.77	1.61	1.34	1.79
Fin	2.45	2.04	2.07	2.35
Fra	1.84	1.68	1.48	1.83
Ger	1.90	1.48	1.45	1.86
Gre	2.31	2.18	1.80	2.28
Ita	1.50	1.01	1.01	1.34
Jap	1.77	2.37	1.89	2.46
Kor	6.67	6.36	6.16	6.34
Neth	2.18	1.82	1.79	2.21
Nor	2.76	2.29	2.15	2.66
Por	2.68	2.46	2.22	2.55
Spa	2.89	2.74	2.32	3.13
Swe	2.35	2.00	2.00	2.51
UK	2.57	2.24	2.07	2.53
US	2.93	2.99	2.42	2.86

Notes: [a]Except for the cases of Bol, Col, CR, Mex, Ven, Den, Ger, Gre and Por the natural rate of growth in all countries was retrieved from the IV estimation results. The natural rate of growth in these 9 countries was retrieved from the OLS estimates (see Table 1); [b]CDP included as additional regressor; [c]Imposing the CDP with unit coefficient.

Table 3. Estimates of equations (3) and (4) using the first dummy variable

	OLS			AMG[1][a]		AMG[2][b]		PRS		
	α_0	α_1	Adj. R^2	α_0	α_1	α_0	α_1	α_0^*	α_1^*	Adj. R^2
LA										
Arg	-2.404	10.040**	0.76	-2.542^	9.219**	-2.218*	9.216**	-2.563*	10.003**	0.77
Bol	0.274	4.219**	0.58	-0.029	4.287**	0.212	4.133**	0.199	4.191**	0.63
Bra	0.405	3.785**	0.71	0.237	3.866**	0.431	3.633**	0.028	4.299**	0.77
Chi	2.583**	4.389**	0.73	1.382	4.169*	0.959	4.562**	2.494**	3.923**	0.71
Col	2.658**	2.595**	0.73	4.373*	-0.093	2.523**	2.007**	2.768**	2.262**	0.82
CR	2.069*	4.331**	0.57	-0.092	5.427**	-0.198	5.503**	1.598^	4.640**	0.57
Ecu	0.575	4.712**	0.56	0.009	4.752**	0.247	4.629**	0.447	4.513**	0.58
Mex	0.467	4.005**	0.78	0.708	3.660**	0.837	3.387**	0.108	3.919**	0.75
Nic	-2.483	6.677**	0.62	-2.399*	6.576**	-1.999*	6.056**	-1.910	6.405**	0.60
Par	-0.326	5.550**	0.60	0.394	4.620**	0.138	5.008**	-0.692	5.337**	0.77
Peru	-1.333	8.343**	0.68	-1.079	7.436**	-1.680	8.012**	-1.101	7.883**	0.77
Uru	-0.365	6.590**	0.82	0.251	5.716**	0.373	5.752**	-1.180	6.926**	0.80
Ven	-0.655	5.860**	0.74	0.059	5.068**	-0.283	5.466**	-0.962	5.856**	0.79
OECD										
Aus	1.935**	2.236**	0.71	1.022^	2.885**	1.781**	2.298**	1.733**	2.349**	0.59
Bel	1.102**	1.878**	0.66	1.228**	1.604**	1.423**	1.633**	0.939**	1.892**	0.66
Can	1.614**	1.751**	0.86	1.587**	1.641**	1.477**	2.145**	1.585**	1.556**	0.85
Den	0.963*	1.704**	0.70	1.091**	2.028**	1.176**	2.378**	0.918**	1.708**	0.73
Fin	0.381	3.015**	0.69	0.810	2.696**	0.876	2.579**	0.410	2.613**	0.85
Fra	1.074**	1.596**	0.49	1.264**	1.706**	1.514**	1.876**	0.862**	1.704**	0.55
Ger	0.739	2.545**	0.48	1.025**	2.578**	1.196**	3.153**	0.410	2.670**	0.46
Gre	0.479	3.397**	0.86	0.381	3.377**	0.594	3.544**	0.229	3.622**	0.87
Ita	0.170	2.362**	0.45	0.915**	3.054**	0.849**	2.968**	-0.163	2.247**	0.65
Jap	1.585**	1.882*	0.41	0.714^	3.483**	0.796**	3.886**	0.869*	3.576**	0.77
Kor	4.404**	4.741**	0.75	-0.856	7.701^	2.874	4.125*	4.339**	4.029**	0.74
Neth	0.872*	2.312**	0.58	1.049**	2.005**	1.125**	2.089**	0.883*	2.267**	0.63
Nor	1.477**	2.603**	0.75	1.308**	2.484**	1.507**	2.215**	1.366**	2.659**	0.72
Por	1.325**	2.467**	0.80	1.226**	2.463**	1.314**	2.543**	1.356**	2.472**	0.82
Spa	2.598**	1.192*	0.84	2.819**	0.425	2.163**	1.278*	2.617**	1.135**	0.92
Swe	1.219**	2.417**	0.70	1.409**	2.103**	1.834**	1.655**	0.953*	2.492**	0.66
UK	1.112**	2.412**	0.73	1.071*	2.467**	1.392**	2.134**	1.179**	2.326**	0.85
US	2.115**	1.552**	0.88	1.776**	1.563**	1.609**	1.676**	2.097**	1.505**	0.89

Notes: [a]CDP included as additional regressor; [b]Imposing the CDP with unit coefficient.
^,*, and ** respectively denote rejection of the null hypothesis at the 10%, 5%, and 1% confidence levels.

Table 4. Estimates of equations (3) and (4) using the second dummy variable

	OLS			AMG[1][a]		AMG[2][b]		PRS		
	α_0	α_1	Adj. R^2	α_0	α_1	α_0	α_1	α_0^*	α_1^*	Adj. R^2
LA										
Arg	-0.640	7.471**	0.74	-0.569	6.514**	-0.719	6.899**	-0.748	7.147**	0.72
Bol	-0.213	4.380**	0.62	-0.161	4.229**	-0.058	3.923**	-0.205	4.409**	0.63
Bra	0.862	2.616**	0.57	1.071^	2.306**	1.077^	2.298**	0.817	2.759**	0.60
Chi	2.716**	3.643**	0.70	2.359*	2.819*	2.231*	2.933*	2.717**	3.732**	0.72
Col	3.331**	1.016	0.60	3.117**	0.837	3.148**	0.757	2.810**	1.203^	0.58
CR	1.963*	3.714**	0.54	0.968	3.775**	1.074	3.558**	1.903*	3.882**	0.55
Ecu	2.176**	1.863^	0.04	1.886*	1.811	1.896*	1.805	1.779*	2.139^	0.17
Mex	1.291*	3.032**	0.71	1.329**	2.687**	1.348**	2.529**	1.190^	2.772**	0.68
Nic	-1.419	5.054*	0.45	0.154	3.497*	0.229	3.131^	-1.562	5.362**	0.49
Par	1.074	3.395**	0.38	1.302	2.479*	1.191	2.762*	0.794	3.277**	0.63
Peru	0.301	5.720**	0.40	-1.565	7.253**	-1.646	7.466**	0.560	5.157**	0.50
Uru	-0.735	5.578**	0.73	-0.582	5.003**	-0.599	5.064**	-1.445	6.099**	0.72
Ven	1.181^	3.134^	0.66	1.730^	1.321	1.662^	1.589	1.013	2.893*	0.71
OECD										
Aus	2.593**	1.314*	0.20	2.109**	1.727*	2.420**	1.069	2.583**	1.218*	0.20
Bel	1.128^	1.015	0.35	1.399**	1.082*	1.391**	1.088*	1.282**	0.949^	0.34
Can	2.428**	-0.028	0.75	2.326**	0.221	2.231**	0.090	2.523**	-0.005	0.76
Den	1.177**	1.377**	0.68	1.479**	1.017	1.385**	1.155	1.125**	1.367**	0.70
Fin	0.893	2.231^	0.62	1.718**	1.191	1.695**	1.229	1.187	1.734^	0.75
Fra	1.362**	1.319**	0.36	1.449**	1.809**	1.388**	1.822**	1.229**	1.463**	0.49
Ger	0.985	1.769^	0.29	1.313**	2.987**	1.322**	2.987**	0.802	1.876*	0.31
Gre	0.619	2.840**	0.75	1.027*	2.767**	0.894^	2.669**	0.133	3.247**	0.77
Ita	0.257	2.069**	0.30	0.948**	2.842**	0.954**	2.826**	0.433	1.659**	0.52
Jap	1.177**	3.365**	0.68	0.793*	3.830**	0.712*	3.928**	1.183**	3.342**	0.67
Kor	4.595**	4.001**	0.70	2.674	3.988	2.719	3.902	4.594**	3.515**	0.70
Neth	0.812	2.553**	0.52	1.235**	2.336**	1.221**	2.309**	0.923^	2.235**	0.57
Nor	1.598**	2.168**	0.57	1.608**	2.109**	1.593**	1.948**	1.551**	2.256**	0.58
Por	1.409**	2.176**	0.77	1.438**	2.262**	1.385**	2.026**	1.507**	2.174**	0.78
Spa	2.955**	0.485	0.83	2.541**	0.921^	1.779**	1.369*	2.841**	0.407	0.87
Swe	2.346*	0.627	0.52	2.339**	0.219	2.339**	0.217	1.959*	0.784	0.49
UK	1.417^	1.970*	0.67	1.208*	2.055**	1.062*	2.114**	1.119^	2.187**	0.76
US	2.340**	1.010	0.80	2.249**	1.062*	1.648**	1.625**	2.250**	1.185*	0.82

Notes: [a]CDP included as additional regressor; [b]Imposing the CDP with unit coefficient.
^,*, and ** respectively denote rejection of the null hypothesis at the 10%, 5%, and 1% confidence levels.

Table 5. Potential rates of growth in low and high growth periods

	Low growth periods								High growth periods							
	First dummy				Second dummy				First dummy				Second dummy			
	OLS	AMG[1][a]	AMG[2][b]	PRS	OLS	AMG[1][a]	AMG[2][b]	PRS	OLS	AMG[1][a]	AMG[2][b]	PRS	OLS	AMG[1][a]	AMG[2][b]	PRS
LA																
Arg	-	-2.54	-2.22	-2.56	-	-	-	-	10.04	6.68	7.00	7.44	7.47	6.51	6.90	7.15
Bol	-	-	-	-	-	-	-	-	4.22	4.29	4.13	4.19	4.38	4.23	3.92	4.41
Bra	-	-	-	-	-	1.07	1.08	-	3.79	3.87	3.63	4.30	2.62	3.38	3.38	2.76
Chi	2.58	-	-	2.49	2.72	2.36	2.23	2.72	6.97	4.17	4.56	6.42	6.36	5.18	5.16	6.45
Col	2.66	4.37	2.52	2.77	3.33	3.12	3.15	2.81	5.25	-	4.53	5.03	-	-	-	4.01
CR	2.07	-	-	1.60	1.96	-	-	1.90	6.40	5.43	5.50	6.24	5.68	3.78	3.56	5.79
Ecu	-	-	-	-	2.18	1.89	1.90	1.78	4.72	4.75	4.63	4.51	4.04	-	-	3.92
Mex	-	-	-	-	1.29	1.33	1.35	1.19	4.01	3.66	3.39	3.92	4.32	4.02	3.88	3.96
Nic	-	-2.40	-2.00	-	-	-	-	-	6.68	4.18	4.06	6.41	5.05	3.50	3.13	5.36
Par	-	-	-	-	-	-	-	-	5.55	4.62	5.01	5.34	3.40	2.48	2.76	3.28
Peru	-	-	-	-	-	-	-	-	8.34	7.44	8.01	7.88	5.72	7.25	7.47	5.16
Uru	-	-	-	-	-	-	-	-	6.59	5.72	5.75	6.93	5.58	5.00	5.06	6.10
Ven	-	-	-	-	1.18	1.73	1.66	-	5.86	5.07	5.47	5.86	4.32	-	-	2.89
OECD																
Aus	1.94	1.02	1.78	1.73	2.59	2.11	2.42	2.58	4.17	3.91	4.08	4.08	3.91	3.84	-	3.80
Bel	1.10	1.23	1.42	0.94	1.13	1.40	1.39	1.28	2.98	2.83	3.06	2.83	-	2.48	2.48	2.23
Can	1.61	1.59	1.48	1.59	2.43	2.33	2.23	2.52	3.37	3.23	3.62	3.14	-	-	-	-
Den	0.96	1.09	1.18	0.92	1.18	1.48	1.39	1.13	2.67	3.12	3.55	2.63	2.55	-	-	2.49
Fin	-	-	-	-	-	1.72	1.70	-	3.02	2.70	2.58	2.61	2.23	-	-	1.73
Fra	1.07	1.26	1.51	0.86	1.36	1.45	1.39	1.23	2.67	2.97	3.39	2.57	2.68	3.26	3.21	2.69
Ger	-	1.03	1.20	-	-	1.31	1.32	-	2.55	3.60	4.35	2.67	1.77	4.30	4.31	1.88
Gre	-	-	-	-	-	1.03	0.89	-	3.40	3.38	3.54	3.62	2.84	3.79	3.56	3.25
Ita	-	0.92	0.85	-	-	0.95	0.95	-	2.36	3.97	3.82	2.25	2.07	3.79	3.78	1.66
Jap	1.59	0.71	0.80	0.87	1.18	0.79	0.71	1.18	3.47	4.20	4.68	4.45	4.54	4.62	4.64	4.53
Kor	4.40	-	2.870	4.34	4.60	-	-	4.59	9.15	7.70	4.13	8.37	8.60	-	-	8.11
Neth	0.87	1.05	1.13	0.88	-	1.24	1.22	0.92	3.18	3.05	3.21	3.15	2.55	3.57	3.53	3.16
Nor	1.48	1.31	1.51	1.37	1.60	1.61	1.59	1.55	4.08	3.79	3.72	4.03	3.77	3.72	3.54	3.81
Por	1.33	1.23	1.31	1.36	1.41	1.44	1.39	1.51	3.79	3.69	3.86	3.83	3.59	3.70	3.41	3.68
Spa	2.60	2.82	2.16	2.62	2.96	2.54	1.78	2.84	3.79	-	3.44	3.75	-	3.46	3.15	-
Swe	1.22	1.41	1.83	0.95	2.35	2.34	2.34	1.96	3.64	3.51	3.49	3.45	-	-	-	-
UK	1.11	1.07	1.39	1.18	1.42	1.21	1.06	1.12	3.52	3.54	3.53	3.51	3.39	3.26	3.18	3.31
US	2.12	1.78	1.61	2.10	2.34	2.25	1.65	2.25	3.67	3.34	3.29	3.60	-	3.31	3.27	3.44

Notes: [a]CDP included as additional regressor; [c]Imposing the CDP with unit coefficient.
- denotes that the estimate is not reported since it was found to be statistically non-significant (see Tables 2 and 3).

Table 6. Output gap measures in low and high growth periods

	Low growth periods: $g_n^L - g_n$									High growth periods: $g_n^H - g_n$								
	First dummy				Second dummy				**Average**	First dummy				Second dummy				**Average**
	OLS	AMG[1][a]	AMG[2][b]	PRS	OLS	AMG[1][a]	AMG[2][b]	PRS		OLS	AMG[1][a]	AMG[2][b]	PRS	OLS	AMG[1][a]	AMG[2][b]	PRS	
LA																		
Arg	-	-4.49	-4.82	-5.62	-	-	-	-	**-**	6.96	4.73	4.40	4.38	4.39	4.56	4.30	4.09	**4.73**
Bol	-	-	-	-	-	-	-	-	**-**	1.22	2.00	1.93	1.44	1.38	1.94	1.72	1.66	**1.66**
Bra	-	-	-	-	-	-0.93	-0.95	-	**-**	0.91	1.87	1.60	1.84	-0.26	1.38	1.35	0.30	**1.32**
Chi	-2.23	-	-	-2.25	-2.09	-1.69	-2.07	-2.02	**-2.06**	2.16	0.12	0.26	1.68	1.55	1.13	0.86	1.71	**1.18**
Col	-1.00	0.98	-0.69	-0.79	-0.33	-0.27	-0.06	-0.75	**-0.56**	1.59	-	1.32	1.47	-	-	-	0.45	**1.21**
CR	-2.11	-	-	-2.58	-2.22	-	-	-2.28	**-2.30**	2.22	1.84	1.78	2.06	1.50	0.19	-0.16	1.61	**1.60**
Ecu	-	-	-	-	-0.83	-0.77	-0.69	-1.06	**-0.84**	1.71	2.09	2.04	1.67	1.03	-	-	1.08	**1.60**
Mex	-	-	-	-	-1.23	-0.81	-0.73	-1.35	**-1.03**	1.49	1.52	1.31	1.38	1.80	1.88	1.80	1.42	**1.58**
Nic	-	-4.06	-3.45	-	-	-	-	-	**-**	4.63	2.52	2.61	4.51	3.00	1.84	1.68	3.46	**3.03**
Par	-	-	-	-	-	-	-	-	**-**	2.56	2.29	2.39	2.66	0.41	0.15	0.14	0.60	**1.40**
Peru	-	-	-	-	-	-	-	-	**-**	5.31	5.08	5.26	4.76	2.69	4.89	4.72	2.04	**4.34**
Uru	-	-	-	-	-	-	-	-	**-**	4.66	4.29	4.02	4.64	3.65	3.57	3.33	3.81	**4.00**
Ven	-	-	-	-	-1.27	-0.01	-0.35	-	**-**	3.41	3.33	3.46	3.72	1.87	-	-	0.75	**2.76**
OECD																		
Aus	-1.32	-2.06	-1.03	-1.50	-0.67	-0.97	-0.39	-0.65	**-1.07**	0.91	0.83	1.27	0.85	0.65	0.76	-	0.57	**0.83**
Bel	-0.85	-0.30	-0.01	-0.91	-0.82	-0.13	-0.04	-0.57	**-0.45**	1.03	1.30	1.63	0.98	-	0.95	1.05	0.38	**1.05**
Can	-0.95	-1.02	-0.65	-0.93	-0.13	-0.28	0.10	0	**-0.57**	0.81	0.62	1.49	0.62	-	-	-	-	**0.89**
Den	-0.81	-0.52	-0.16	-0.87	-0.59	-0.13	0.05	-0.66	**-0.53**	0.90	1.51	2.21	0.84	0.78	-	-	0.70	**1.16**
Fin	-	-	-	-	-	-0.32	-0.37	-	**-**	0.57	0.66	0.51	0.26	-0.22	-	-	-0.62	**0.50**
Fra	-0.77	-0.42	0.03	-0.97	-0.48	-0.23	-0.09	-0.60	**-0.51**	0.83	1.29	1.91	0.74	0.84	1.58	1.73	0.86	**1.22**
Ger	-	-0.45	-0.25	-	-	-0.17	-0.13	-	**-0.25**	0.65	2.12	2.90	0.81	-0.13	2.82	2.86	0.02	**1.74**
Gre	-	-	-	-	-	-1.15	-0.91	-	**-**	1.09	1.20	1.74	1.34	0.53	1.61	1.76	0.97	**1.28**
Ita	-	-0.09	-0.16	-	-	-0.06	-0.06	-	**-0.09**	0.86	2.96	2.81	0.91	0.57	2.78	2.77	0.32	**1.75**
Jap	-0.18	-1.66	-1.09	-1.59	-0.59	-1.58	-1.18	-1.28	**-1.14**	1.70	1.83	2.79	1.99	2.77	2.25	2.75	2.07	**2.27**
Kor	-2.27	-	-3.29	-2.00	-2.07	-	-	-1.75	**-2.28**	2.48	1.34	-2.03	2.03	1.93	-	-	1.77	**1.91**
Neth	-1.31	-0.77	-0.66	-1.33	-	-0.58	-0.57	-1.29	**-0.93**	1.00	1.23	1.42	0.94	0.37	1.75	1.74	0.95	**1.18**
Nor	-1.28	-0.98	-0.64	-1.29	-1.16	-0.68	-0.56	-1.11	**-0.96**	1.32	1.50	1.57	1.37	1.01	1.43	1.39	1.15	**1.34**
Por	-1.35	-1.23	-0.91	-1.19	-1.27	-1.02	-0.83	-1.04	**-1.11**	1.11	1.23	1.64	1.28	0.91	1.24	1.19	1.13	**1.22**
Spa	-0.29	0.08	-0.16	-0.51	0.07	-0.20	-0.54	-0.29	**-0.33**	0.90	-	1.12	0.62	-	0.72	0.83	-	**0.84**
Swe	-1.13	-0.59	-0.17	-1.56	0	0.34	0.34	-0.55	**-0.67**	1.29	1.51	1.49	0.94	-	-	-	-	**1.31**
UK	-1.46	-1.17	-0.68	-1.35	-1.15	-1.03	-1.01	-1.41	**-1.16**	0.95	1.30	1.46	0.98	0.82	1.02	1.11	0.78	**1.05**
US	-0.81	-1.21	-0.81	-0.76	-0.59	-0.74	-0.77	-0.61	**-0.79**	0.74	0.35	0.87	0.74	-	0.32	0.85	0.58	**0.64**

Notes: [a]CDP included as additional regressor; [b]Imposing the CDP with unit coefficient.
- denotes that the estimate is not reported since it was found to be statistically non-significant (see Table 5).

A Unemployment rates coverage

Table A1. Databases employed for the unemployment rate series

LA	
Arg	Ball et al. (2013): 1980-2007; ECLAC: 2008-2011
Bol	Ball et al. (2013): 1989-2006; ECLAC: 1980-1988 and 2007-2011
Bra	Ball et al. (2013): 1982-2007; ECLAC: 1980-1981 and 2008-2011
Chi	Ball et al. (2013): 1980-2007; ECLAC: 2008-2011
Col	Ball et al. (2013): 1980-2007; ECLAC: 2008-2011
CR	Ball et al. (2013): 1980-2007; ECLAC: 2008-2011
Ecu	Ball et al. (2013): 1990-2007; ECLAC: 1980-1989 and 2008-2011
Mex	Ball et al. (2013): 1980-2007; ECLAC: 2008-2011
Nic	ECLAC: 1980-2011
Par	Ball et al. (2013): 1980-2007; ECLAC: 2008-2011
Peru	Ball et al. (2013): 1980-2007; ECLAC: 2008-2011
Uru	Ball et al. (2013): 1980-2007; ECLAC: 2008-2011
Ven	Ball et al. (2013): 1980-2007; ECLAC: 2008-2011
OECD	
Aus	OECD: 1980-2011
Bel	IMF: 1980-1982; OECD: 1983-2011
Can	OECD: 1980-2011
Den	IMF: 1980-1982; OECD: 1983-2011
Fin	OECD: 1980-2011
Fra	IMF: 1980-1982; OECD: 1983-2011
Ger	OECD: 1980-2011
Gre	IMF: 1980-1982; OECD: 1983-2011
Ita	OECD: 1980-2011
Jap	OECD: 1980-2011
Kor	OECD: 1980-2011
Neth	OECD: 1980-2011
Nor	OECD: 1980-2011
Por	OECD: 1980-2011
Spa	OECD: 1980-2011
Swe	OECD: 1980-2011
UK	IMF: 1980-1983; OECD: 1984-2011
US	OECD: 1980-2011

B Derivation of equation (15)

Let us assume for simplicity that d=2. From equation (14) we have that:

$$\begin{aligned}
\int \left\{s^2(t,\delta)\right\}^2 \mathrm{d}t &= \int \left[\frac{\partial^2 s(t,\delta)}{\partial(t,\delta)^2}\right]^2 \mathrm{d}t && \text{(B.1)}\\
&= \int \left[\frac{\partial^2 \sum_{k=1}^{q} \delta_k b_k(t)}{\partial(t,\delta)^2}\right]^2 \mathrm{d}t && \text{(B.2)}\\
&= \int \left[\delta^{\mathbf{T}}\mathbf{b}(\mathbf{t})\right]^2 \mathrm{d}t && \text{(B.3)}\\
&= \int \left[\delta^{\mathbf{T}}\mathbf{b}(\mathbf{t})\mathbf{b}(\mathbf{t})^{\mathbf{T}}\delta\right] \mathrm{d}t && \text{(B.4)}\\
&= \delta^{\mathbf{T}} \left(\int \left[\mathbf{b}(\mathbf{t})\mathbf{b}(\mathbf{t})^{\mathbf{T}}\right] \mathrm{d}t\right) \delta && \text{(B.5)}\\
&= \delta^{\mathbf{T}}\mathbf{S}\delta && \text{(B.6)}
\end{aligned}$$

This is the result shown in equation (15).