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ON THE INTERACTION BETWEEN ECONOMIC GROWTH AND BUSINESS CYCLES

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The present paper studies the interaction between short-run business cycle fluctuations and economic growth at the empirical level. We identify a measure of potential output with that rate of growth consistent with a constant unemployment rate, and we estimate the effects of GDP growth rates on the latter in 13 Latin American and 18 OECD countries during the period 1981–2011. The results of both parametric (OLS/IV and a panel estimator that allows for parameter heterogeneity and cross-section dependence) and nonparametric (a penalized regression spline estimator) econometric techniques show that the measure of potential output experiences positive (negative) changes in periods of high (low) growth in the majority of countries. However, in contrast to the sample of OECD countries, we find that less than half of the sample of Latin American countries experience statistically significant changes in this measure of potential output in periods of low growth.

Keywords: Growth and Cycles, Potential Rate of Growth, Rate of Growth Consistent with a Constant Unemployment Rate, Hysteresis

1. INTRODUCTION

Postwar economics has devoted a significant amount of research to the study of the interaction between short-run business cycle fluctuations and potential or long-run economic growth, ever since the finding of stochastic trends in most macroeconomic series. The present paper estimates the effects that business cycle fluctuations generate on the rate of growth consistent with a constant unemployment rate. The latter can be identified with a measure of potential output growth, because it represents the sum of labor force and labor 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 OLS) and instrumental variable (henceforth IV) methods;

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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, so that 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 because, in contrast to the sample of OECD countries, less than half of the sample of LA countries (5 out of 13 countries) experience statistically significant changes in this measure of potential output in periods of low growth.

Besides this Introduction, the rest of the paper comprises four sections. Section 2 reviews the theoretical and empirical literature on the interaction between business cycles and economic growth. Section 3 presents the empirical strategy (Subsection 3.1) and provides a description of the techniques employed in the present context (Subsection 3.2). The key empirical findings are presented and discussed in Section 4. The main conclusions and some potentially relevant areas for 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 economies. However, as Keating (2013) has mentioned, it is possible to find various economic theories that permit different types of long-run non-neutrality at the theoretical level. Two well-known examples are non-superneutrality-type models [Tobin (1965); Orphanides and Solow (1990)] and fiscal policy models that allow long-run effects [Baxter and King (1993)]. The former show that short-run monetary factors and portfolio decisions modify the capital stock, the output per worker, and the interest rate in the steady state [Tobin (1965)] 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 [Orphanides and Solow (1990)]. In the same vein, Baxter and King (1993) 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. More recently, Kapadia (2005) and Kienzler and Schmid (2014) have studied the consequences of hysteresis in potential output for monetary policy by modifying the standard New Keynesian model in order to analyze (1) cost-push shocks under a range of different Phillips curve specifications [Kapadia (2005)] and (2) productivity and monetary shocks under different degrees of hysteresis [Kienzler and Schmid (2014)].

On the other hand, models following the learning-by-doing approach [Stadler (1990); Stiglitz (1994); Maliar and Maliar (2004); Blackburn and Pelloni (2005); Barlevy (2007); Comin (2009)] highlight the procyclical 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 such pioneering model is Stadler (1990), who showed that if technology is endogenous, changes in aggregate demand can result in permanent changes in productivity, employment and output. Recent contributions have incorporated financial constraints [Stiglitz (1994)]; uncertainty at the aggregate level [Maliar and Maliar (2004)]; nominal rigidities and wage contracts [Blackburn and Pelloni (2005)]; dynamic externalities [Barlevy (2007)]; endogenous diffusion of technologies [Comin (2009)]; and spillover effects from knowledge accumulation and variation in technology diffusion rates [Bianchi and Kung (2014)]. Sedgley and Elmslie (2013) also explore the out-of-steady-state behaviour and the stability of steady state growth rates in semiendogenous and endogenous growth models, finding that the path of transition to the steady state is important in order to study economic growth.

Growth and fluctuations have also been studied by models within the Schumpeterian tradition. As mentioned by Christopoulos and León-Ledesma (2014), 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 [Hall (1991); Saint-Paul (1997); Aghion and Saint-Paul (1998)] stresses that investment in productivity-improving activities and normal production activities are substitutes rather than complements, so that productivity-improving activities can be carried out at the expense of normal production activities. Therefore, these models consider that productivity may be countercyclical or procyclical, depending on whether productivity-improving activities have a disruptive effect on production or can be bought in the market without affecting current production [Aghion and Saint-Paul (1998)]. Recently, Nuño (2011) has introduced a calibrated dynamic stochastic general equilibrium model with Schumpeterian endogenous growth that explains the observed procyclicality of research and development.

The cleansing effect literature [Davis and Haltiwanger (1992); Caballero and Hammour (1994, 2005)] assumes that general profitability falls during recessions, so that business cycles "clean" the economy of 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 assumes 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 units is reduced. The theoretical and empirical results presented by Caballero and Hammour (2005) 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 are also a variety of models explicitly linking endogenous short-run fluctuations and endogenous long-run growth in a unified setting. Here, 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 developed by Evans et al. (1998), where 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 (1999) 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 nonmonotonically related to the length of the cycle. Other examples within this stream of literature include quality-ladder growth models [Francois and Lloyd-Ellis (2003)], portfolio approach models [Matsuyama (1999); Wälde (2005)], models with gradual diffusion of innovation [Furukawa (2007)], models with distortionary taxes [Posch and Wälde (2011)], and models with research and development subsidies [Furukawa (2013)].

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.

The estimation results presented by Kandil (1998) 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 than in more developed countries; and (3) the aggregate supply curve also appears steeper in the face of positive demand shocks than of 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 (2000a, 2000b, 2002). 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 (2013) interpreted 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 postwar United States (henceforth U.S.) 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 (2003) 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 (2013) shows that shocks have permanent persistent negative effects on U.S. GDP—especially large recessionary ones; whereas the estimations of univariate and multivariate trend–cycle decomposition models of GDP by Guérin et al. (2015) show evidence of regime changes in the growth of potential output for a few recession periods around 1974 and 2008 in the euro area.

Likewise, Haltmaier (2012) examines whether the growth of potential output (proxied by Hodrick–Prescott filter trends) is affected by recessions using panel regressions; whereas Reifschneider et al. (2013) use an unobserved component model to estimate the effect of the recent financial crisis in the United States. The former study finds that the depth of a recession contributes to the reduction in trend output for advanced economies, whereas the length is important for emerging countries (which means that recessions that are deeper and/or longer than the average may have a substantial effect on the level of trend output); whereas the latter finds that the level of potential GDP was about 6% below its precrisis trend in the first quarter of 2013 (with a 95% confidence interval ranging from 3.8 to 8.1%).

Recently, the empirical literature has also tried to identify the effects of recessions on different components of long-run growth. DeLong and Summers (2012) calculate 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.[1] Similarly, Fernald (2014) finds that the end of exceptional growth implies slower growth in potential output and that growth in aggregate demand has also been weak; whereas the results of the stochastic production frontier analysis presented by Christopoulos and León-Ledesma (2014) show that recessions have significant negative effects on total factor productivity (henceforth TFP) from the last year of a recession up to four years after for a panel of 70 countries during the period 1960–2000.

Finally, it is possible to find various studies analyzing the medium- and long-run effects of financial crisis on output. Regarding the medium-term dynamics of output following banking crisis, Abiad et al. (2009) consider a sample of 88 banking crises 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 precrisis 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–labor ratio. In the same vein, Reinhart and Rogoff (2014) examine the consequences of 100 systemic banking crises spanning nearly two centuries on real per capita GDP, finding that, on the average, it takes about eight years to reach the precrisis level of income (the median is about 6.5 years).

With respect to the long-run effects of financial crisis on output, Boyd et al. (2005) calculate that a sample of 23 countries countries experienced reductions in current and future output whose discounted present value was bounded between 63% and 302% of real GDP in the final precrisis year, and that only 4 out of 23 sample countries reattained their precrisis trend levels of output within 17 years of a crisis onset. Cerra and Saxena (2008) 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 conclude that less than 1% of the deepest output loss is regained by the end of ten years following a banking crisis. Papell and Prodan (2012) develop a statistical methodology to identify and analyze slumps, finding that, among advanced countries, the return to potential GDP following recessions associated with financial crises (9 years) is much longer than the return following other postwar recessions prior to 2007 (1.5 years). They also find that the magnitude of the recessions following financial crises for emerging markets is larger than that for advanced economies, and that its duration is comparable with recessions not associated with financial crises 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 (2012) calculate that financial crises lower potential output by around 1.5–2.4% on the average, with most of the impact coming from the effect on capital; whereas Bijapur (2012) concludes that inflationary pressures tend to be stronger in the aftermath of financial crisis compared with noncrisis economic downturns, indicating impairment in productive potential. Recently, Ball (2014) has estimated the long-term effects of the global recessions of 2008–2009 on output in 23 OECD countries. He finds that the average loss (weighted by economy size) is 8.4%, thus concluding that most countries have experienced strong hysteresis effects: shortfalls of actual output from prerecession trends have reduced potential output almost one for one.

Thus, the picture arising from this review is that there are a whole host of mechanisms—explored at both the theoretical and empirical levels—through which short-run business cycle fluctuations can affect long-run or potential economic growth. These mechanisms play a role in different factors that generate hysteresis effects, such as resource reallocation, industrial and firm-level restructuring, innovation, learning-by-doing and labor productivity, capital investment, implications for the equilibrium rates of employment and/or labor force participation rates, and credit constraints faced by firms.

3. EMPIRICAL STRATEGY AND ECONOMETRIC TECHNIQUES EMPLOYED

3.1. Empirical Strategy

Different studies [Thirlwall (1969); León-Ledesma and Thirlwall (2002); Schnabel (2002); Knotek (2007); IMF (2010)] 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) because this estimate represents the minimum level of output growth needed to reduce u_t given labor force and labor productivity growth.[2]

As Barreto and Howland (1993) emphasize, 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:[3]

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

where in model (1) β represents the Okun coefficient on unemployment and $\varepsilon_{1,t}$ depicts the 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 $g_n = \alpha$.[4]

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

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

where in model (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 model (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.

To study the interaction between the estimated g_n and g_t, we follow the econometric specifications proposed by León-Ledesma and Thirlwall (2002) and Lanzafame (2010). Regarding the linear model depicted in (1), two dummy variables—both intercept and slope—that identify boom periods are introduced as follows:

$$g_t = \alpha_0 + \alpha_1(D_t) - \beta_0(\Delta u_t) + \beta_1(D_t * \Delta u_t) + \varepsilon_{3,t}, \tag{3}$$

where in model (3) we have that D_t is the dummy variable that adopts a value of one ($D_t = 1$) in periods of growth buoyancy and zero otherwise; and $D_t * \Delta u_t$ 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 (2) is reestimated after the introduction of the respective D_t:

$$g_t = \alpha_0^* + \alpha_1^*(D_t) - \beta_{1,t}(\Delta u_t) + \varepsilon_{4,t}. \tag{4}$$

From models (3) and (4), it is possible to identify two different g_n's 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 model (3) and $\alpha_0^* + \alpha_1^*$ in model (4), whereas the other g_n corresponds to the low-growth regime (henceforth g_n^{L}), defined by the intercept term: α_0 in model (3) and α_0^* in model (4).[5]

Hence, if the respective parameter estimates that determine g_n^{H} and g_n^{L} [retrieved from models (3) and (4)] are found to be statistically significantly higher or lower (depending on the case) than the original estimate of g_n [obtained from models (1) and (2)], then it is possible to say that the estimated g_n experienced changes during the expansion and contraction periods as a result of the interaction with g_t. In this sense, the difference between g_n^{H} and 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 can be regarded as a measure of the output gap in low-growth periods.

To construct the dummy variables, we have identified periods of growth buoyancy following two different estimation procedures that try to show the robustness of the results:

1. When $g_t > g_n$, we compare g_t with the estimate of g_n [obtained from models (1) and (2)] in order to construct both intercept and slope dummy variables.
2. When $g_{3\mathrm{MA},t} > g_{\mathrm{AVE},t}$, where $g_{3\mathrm{MA},t}$ represents a three-year moving average of g_t, and $g_{\mathrm{AVE},t}$ is the average g_t during the period of study, we compare $g_{3\mathrm{MA},t}$ with $g_{\mathrm{AVE},t}$ in order to construct both dummy variables, which allows us to identify expansion periods independent of the original estimate of g_n.

To summarize, in this paper we have employed two different two-step estimation procedures to quantify the differences between g_n and g_n^{H} and between g_n and g_n^{L}. In both cases we first estimate g_n using models (1) and (2). Subsequently, as described in points one and two, we construct dummy variables that identify expansion periods. Finally, we estimate models (3) and (4) in order to retrieve the estimates of g_n^{H} and g_n^{L}.

3.2. Econometric Techniques

We have estimated models (1) and (3) using OLS/IV, and panel estimators with general multifactor error structures that take into account parameter heterogeneity and cross-section dependence, whereas models (2) and (4) were estimated via a PRS estimator that allows for time-varying effects.

However, the estimation of models (1) to (4) requires two further clarifications. First, the use of generated dummy variables in models (3) and (4) raises the issue of second stage regressions with generated regressors. As Pagan (1984) and Murphy

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and Topel (1985) explain, two-step procedures fail to account for the fact that imputed regressors are measured with sampling error, so hypothesis tests based on the estimated covariance matrix of the second-step estimator are biased, even in large samples. Therefore, we have employed bootstrapped standard errors (2,000 replications in all cases) to estimate models (3) and (4), which allows us to derive conclusions regarding the statistical significance of the estimated parameters.[6]

Second, both output and unemployment are endogenous variables to a complex system and, therefore, it is necessary to consider the possible endogeneity bias in the estimation of models (1) to (4). We have dealt with the latter only for the OLS estimation of models (1) and (3) because, to the best of our knowledge, the use of IV methods has been explored only for the case of the OLS estimator.[7]

We provide a description of the IV methods employed, the panel estimators, and the PRS estimator.

OLS and IV. Let us illustrate the use of OLS and IV methods using model (1). We first estimated model (1) via OLS employing the following misspecification tests on the estimation results: Breusch–Godfrey serial correlation Lagrange multiplier (henceforth LM) test [Breusch (1978); Godfrey (1978)]; Breusch–Pagan test for heteroskedasticity [Breusch and Pagan (1979)]; Jarque–Bera normality test [Jarque and Bera (1987)]; and Ramsey regression equation specification error test (henceforth RESET) [Ramsey (1969)] for incorrect functional form. The relevant results for these diagnostic tests are discussed in each section.[8]

We then tested for the appropriateness of OLS and the necessity to resort to IV as follows:

1. We reestimated model (1) using as instruments different combinations of the lags (up to two) of Δu_t, the rate of growth of labor productivity (henceforth τ_t), and the rate of growth of total labor force (henceforth l_t), performing a C-statistic—also known as "generalized method of moments (GMM) distance" or "difference-in-Sargan" statistic—type test of endogeneity [Hayashi (2000)] for each possible combination of instruments. 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.[9] Moreover, unlike the traditional Durbin–Wu–Hausman tests, the C-statistic type test of endogeneity is robust to violations of conditional homoskedasticity [Baum et al. (2003, 2007)].[10]
2. In the cases in which we rejected the null hypothesis of the C-test of endogeneity (which states that the suspected endogenous regressor Δu_t can be treated as an exogenous variable), we then tested for overidentifying restrictions using Hansen's J-statistic (which is consistent in the presence of heteroskedasticity and autocorrelation) [Hayashi (2000)].[11] If the instruments employed were valid (i.e., uncorrelated with the error term) according to Hansen's J-statistic (so that the joint null hypothesis that the instruments are valid and that the excluded instruments are correctly excluded from the estimated equation was not rejected), we then retrieved the estimates of g_n using two-stage least squares (henceforth 2SLS) instead of the OLS results.[12]
3. We then tested for weak identification (that is, if instruments are only marginally relevant) in the 2SLS results by comparing the Cragg–Donald F-statistics with the

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Stock and Yogo (2005) weak identification critical values. We also employed an underidentification test—the LM version of the Anderson (1951) canonical correlations test—to evaluate if the instruments used were adequate to identify the model. If evidence of weak identification was found [i.e., if it was not possible to reject the null hypothesis that instruments are only marginally relevant according to Stock and Yogo (2005)] and if it was not possible to reject the null hypothesis of Anderson (1951)'s LM test (which states that the instruments employed are not correlated with the endogenous regressor), we then retrieved the final estimates using Fuller (1977)'s modified limited-information maximum likelihood (henceforth 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 [Stock et al. (2002)].

4. Finally, we (a) tested again for overidentifying restrictions using Hansen's J-statistic and (b) performed the following diagnostic tests on the Fuller's LIML results: Cumby–Huizinga test for autocorrelation [Cumby and Huizinga (1992)]; Pagan–Hall heteroskedasticity test [Pagan and Hall (1983)]; Doornik–Hansen test of multivariate normality [Doornik and Hansen (2008)]; and Ramsey/Pesaran-Taylor RESET test [Pagan and Hall (1983); Pesaran and Taylor (1999)].[13]

Likewise, we followed the procedure described in points one to four in the estimation of model (3) (see Section 4.3).

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 model (1). Following Eberhardt (2012), 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 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 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 [Pesaran and Smith (1995)] can be regarded as a fully heterogeneous-coefficient model because it imposes no cross-group parameter restrictions.[14] 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 pairwise error correlations (henceforth $\widehat{\rho}_{ij}$).[15] We have employed Pesaran (2004)'s CD test, which for the case of balanced panels is specified as follows:

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

On the other hand, Pesaran (2006)'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

$$f_t = \frac{1}{\overline{\mu}} \left[\overline{g_t} - \overline{\alpha} - \overline{\beta}(\overline{\Delta u_t}) - \overline{e_{1,t}} \right], \tag{8}$$

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

$$g_{it} = \alpha_i - \beta_i(\Delta u_{it}) + d_{1,i}(\overline{g_t}) + d_{2,i}(\overline{\Delta u_t}) + e_{1,it}. \tag{9}$$

Thus, in the present context, the CCEMG estimator augments the group-specific regression equation including, besides Δu_{it}, both $\overline{g_t}$ and $\overline{\Delta u_t}$ as additional regressors; and the model parameters are estimated as simple averages of the country-specific estimates: $\widehat{\beta}_{\mathrm{CCEMG}} = \frac{1}{N} \sum_{i=1}^{N} \beta_i$. However, as mentioned by Eberhardt (2012), in empirical application the estimated coefficients on the cross-section-averaged variables and their average estimates are not interpretable in a meaningful way because they exist only to correct for the bias caused by the unobservable common factor.[16]

Eberhardt (2012), Bond and Eberhardt (2013), and Eberhardt and Teal (2014) have recently developed an alternative to the CCEMG with production function estimation in mind: the augmented mean group (henceforth AMG) estimator.[17] 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, where "common" is defined either in the literal sense or as the sample mean country-specific total factor productivity evolution. Nevertheless, the AMG estimator was developed controlling both for capital and for labor force growth. Because the intercept in model (2) represents the rates of growth of labor productivity and labor force, the CDP in our estimates contains the elements that play a role in the rate of growth of capital productivity.

The AMG estimator is implemented in two steps. Using the panel specification of model (1) presented in equation (5), we have the following:

$$\Delta g_{it} = -\beta_i^*[\Delta(\Delta u_{it})] + \sum_{t=2}^{T} c_t(\Delta D_{1,t}) + e_{it}^* \tag{10}$$

$$\Rightarrow \widehat{c_t} \equiv \widehat{\theta_t},$$

$$g_{it} = \alpha_i - \beta_i(\Delta u_{it}) + d_i(\widehat{\theta_t}) + e_{2,it}, \tag{11}$$

$$g_{it} - \widehat{\theta_t} = \alpha_{1,i} - \beta_{1,i}(\Delta u_{it}) + e_{3,it}, \tag{12}$$

where c_t are the coefficients on the $T-1$ year dummies $D_{1,t}$ in first differences, so that c_t represents the estimated CDP; and $e_{2,it}$ and $e_{3,it}$ are error terms.

Hence, in the first stage [that is, equation (10)], a regression model augmented with year dummies $D_{1,t}$ is estimated by first difference OLS and the coefficients on the (differenced) year dummies are collected. These estimated coefficients ($\widehat{c_t}$) are then relabeled as $\widehat{\theta_t}$.[18] 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 it on each group member with unit coefficient by subtracting the estimated process from the dependent variable as depicted in equation (12). Finally, as in the MG and CCEMG estimators, the group-specific model parameters are then averaged across the panel, so that $\widehat{\beta}_{\text{AMG}} = \frac{1}{N}\sum_{i=1}^{N}\widehat{\beta}_i$.

In all the panel estimations presented in this paper, we have employed the outlier-robust procedure developed by Hamilton (1991) in order to attribute less weight to outliers.

Penalized regression spline estimator. Models (2) and (4) are time-varying coefficient models, that is, a special case of a varying-coefficient model [Hastie and Tibshirani (1993)] for which the effect modifier is t [Zanin and Marra (2012)]. We will use only model (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 $\boldsymbol{\delta}$—subject to centering constraints:

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

Therefore, in this approach, the vector of Δu_t effects, $\boldsymbol{\beta} = (\beta_1, \ldots\ldots, \beta_T)_{TX1}$, is modeled as $s(t, \boldsymbol{\delta})$. The use of s is crucial because it allows 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 modeling data using parametric relationships.

The last part of equation (13) shows that s is represented using regression splines [Wood (2006); Marra and Radice (2010)]. 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.[19]

To ensure that the $b_k(t)$ have convenient mathematical properties and good numerical stability it is possible to use thin plate regression splines[20] with a penalized approach. The penalized approach here adopted keeps the number of q fixed at 10 because 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) [Wood (2003)].

Hence, model (2) is fitted as follows:

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

Because regression splines are linear in their model parameters, we have the following result (see Appendix A):

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

where in equations (14) and (15) we have that $\mathbf{g}$ is the vector that contains the annual rates of growth; $\|\mathbf{.}\|$ denotes the Euclidean norm; $\mathbf{X}$ is the model matrix containing $b_k(t)$ interacted with their corresponding Δu_t; $\boldsymbol{\delta}$ now denotes 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 $\boldsymbol{\delta}$ is

$$\widehat{\boldsymbol{\delta}} = (\mathbf{X}^{\mathbf{T}}\mathbf{X} + \lambda\mathbf{S})^{-1}\mathbf{X}^{\mathbf{T}}\mathbf{g}. \quad (\mathbf{16})$$

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

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

where n in equation (17) denotes the number of observations and tr(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

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

$$\widehat{\psi} = \mathbf{A}\mathbf{g}. \quad (\mathbf{19})$$

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

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On the other hand, if we are interested in testing smooth terms for equality to zero [for example, $\mathbf{H_0}$: β_t in model (2)], p-value calculations can be based on the following result:

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

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

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:

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

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

Finally, we have employed the same diagnostic tests mentioned for OLS/IV on the PRS estimation results.

4. EMPIRICAL RESULTS

4.1. Data Description

We have used annual data for the period 1981–2011. 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), South Korea (Kor), the Netherlands (Neth), Norway (Nor), Portugal (Por), Spain (Spa), Sweden (Swe), the United Kingdom (UK), and the United States (US).[21]

For 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 data set constructed by Ball et al. (2013), 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 data set presents missing observations that are necessary

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for the period of study, and therefore it was necessary to resort to the *Economic Commission for Latin American and the Caribbean (ECLAC) Database* (Appendix B shows the details for each country).

Regarding the sample of OECD countries, series were extracted from the OECD electronic database, and missing observations were extracted from the International Monetary Fund (IMF) data and statistics Web page (see also Appendix B).

In the IV estimation of models (1) and (3), we also employed different lags of τ_t and l_t as instruments. Labor productivity was measured as GDP per number of total hours worked. 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. Labor productivity for the rest of the LA countries was calculated as GDP per person employed, and these series were extracted from the World Bank electronic database. On the other hand, labor productivity series for the OECD countries were extracted from the OECD database.

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

4.2. Potential Rate of Growth Estimates

OLS and IV. The estimation results of model (1) obtained 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 in 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 the countries that presented heteroskedasticity problems (Aus, Den, Fin, and Ita). Normality problems were also found in CR, Nic and Ger. The diagnostic tests were satisfied in the other countries.

Regarding the IV estimation results, the null hypothesis of the C-test of endogeneity was rejected (at the 10% level) for the majority of countries—with the exceptions of Bol, Col, CR, Mex, Ven, Den, Ger, Gre, and Por—when the instruments presented in Table 1 were used. These instruments seem to be uncorrelated with the error term, according to Hansen's test of overidentifying restrictions (at the 10% level).

However, with the exception of Fin, the IV estimation results obtained via 2SLS are subject to the problem of weak identification.[22] Moreover, the null hypothesis of the underidentification test was rejected only for Arg, Uru, Bel, Can, Fin, Jap, Spa, Swe, UK, and US. The latter result also suggests that the instruments used may be inadequate to identify the model.

Therefore, with the exception of Fin, the final estimates were obtained from Fuller (1977)'s LIML with $a = 1$. These results satisfied the diagnostic tests

TABLE 1. Estimates of models (1) and (2)

	OLS			IV			AMG[1][a]			AMG[2][b]		PRS		
	α	β	Adj. R^2	α	Instruments used[c]	RMSE	α	β	d	α	β	α^*	β_t[d]	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	—[e]	—[e]	—[e]	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	—[e]	—[e]	—[e]	3.393**	0.816**	0.590*	3.208**	0.731**	3.561**	2.0**	0.54
CR	4.181**	1.487**	0.29	—[e]	—[e]	—[e]	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	—[e]	—[e]	—[e]	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	—[e]	—[e]	—[e]	1.742**	2.299**	1.599**	2.007**	2.421**	2.144**	1.0	0.68

TABLE 1. Continued.

	OLS			IV			AMG[1][a]			AMG[2][b]		PRS		
	α	β	Adj. R^2	α	Instruments used[c]	RMSE	α	β	d	α	β	α^*	β_t[d]	R^2
							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	—[e]	—[e]	—[e]	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	—[e]	—[e]	—[e]	1.480**	0.750*	0.931**	1.448**	0.729*	1.859**	1.0	0.17
Gre	2.311**	1.809**	0.56	—[e]	—[e]	—[e]	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	—[e]	—[e]	—[e]	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

[a]CDP included as additional regressor.
[b]Imposing the CDP with unit coefficient.
[c]Notation: τ_{t-i}=lags of the rate of growth of labor productivity; l_{t-i}=lags of the rate of growth of total labor force; Δu_{t-i}=lags of the change in the percentage level of unemployment rate; $i = 1, 2$.
[d]The estimated degrees of freedom (edf) of the smooth terms are shown.
[e]Not reported because the null hypothesis of the C-statistic type test of endogeneity was not rejected in these cases.
^,*, ** Statistical significance at the 10%, 5%, and 1% levels.

mentioned for OLS and IV in Section 3.2 (point four).[23] Table 1 presents these estimates and reports the root mean squared error (henceforth RMSE) associated with the estimates.

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).[24] Hence, a panel estimate of this type requires estimators robust to the presence of CD, such as the CCEMG and AMG estimators.

We then performed 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 because we only found 15 statistically significant estimates of g_n. The use of the CCEP estimator (using bootstrapped country-clustered standard errors with 2,000 replications) also showed that the intercept term for the panel was statistically nonsignificant. One possible explanation for why the estimated g_n turns out to be statistically nonsignificant when the CCE methodology is employed may be that the latter approach uses a large number of degrees of freedom because, in general, for q regressors it requires $q+1$ cross-sectional averages on the right-hand side. Indeed, as Eberhardt (2012) has mentioned, both the CCEMG and the AMG estimators have been designed for "moderate-T, moderate-N" macro panels. In our case we have a relatively short sample, and therefore a priori we can expect that the CCEMG and CCEP estimators generate fewer significant estimates than the AMG estimator.

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, because the parameter estimates remained unaltered, we only have considered the results of the AMG estimation without country-specific time trends. We report these results in Table 1.

PRS. The results of the estimation of model (2) are also reported in Table 1. Arg, Bol, and UK presented problems of autocorrelation. Therefore, in the first two countries, we included one lag of g_t using an unknown smooth function as parameter, $s(g_{t-1})$; for UK it was also necessary to include Δu_{t-1} as regressor.[25] The other estimates satisfied the diagnostic tests, although heteroskedasticity problems were present in Bol, Aus, and Swe; CR, Ger, and UK presented problems of normality; and Fin and Neth presented problems of correct functional form. In

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general, the results obtained using the PRS approach seem to show adj. R^2 values higher than the ones obtained via the OLS estimator.

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 means that the parameter β_t is statistically time-variant during the period of study in all countries except in these nine cases.

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, and the labor market flexibility, labor market policies, policy implementation timing, and spread of policies in each country. The latter exceeds the purpose of the current paper. However, it is possible to say that, with respect to the sample of OECD countries, the results here obtained corroborate the ones found by Zanin and Marra (2012). For the period 1961–2009, Zanin and Marra (2012) regress Δu_t on g_t [the inverse relationship shown in model (1)], finding time-varying Okun coefficients in their sample of 9 OECD countries (Aus, Fin, Fra, Gre, Ireland, Ita, Neth, Por, and Spa).[26] In the same vein, Daly et al. (2014) have estimated model (1) using quarterly data during the period 1949Q1–2014Q1 for the U.S. economy. Their results show a reduction in the Okun coefficient on unemployment during the subperiod 1981–2011 (from around -2.5 to around -2.0) using rolling regressions (40-quarter rolling window). This reduction is also shown in the results obtained from the PRS estimator because the Okun coefficient is reduced from -2.1 to -1.5.

Summary of results. The estimates of g_n obtained from the different techniques 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 relatively low estimates of g_n compared with the ones obtained via OLS/IV and the PRS in the majority of countries (the only two exceptions being Can and US when the AMG[1] estimation was performed).

4.3. Estimates of the Potential Rates of Growth in Low- and High-Growth Regimes

The estimation results of models (3) and (4) using the different econometric techniques are presented in Tables 3 and 4. The former presents the results obtained using the first dummy variable that identifies expansion periods, whereas the latter presents the estimates 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.[27]

We also estimated model (3) following the IV methods described in Section 3.2, employing the same instruments shown in Table 1 in each country.[28] The null hypothesis of the C-test of endogeneity was rejected in Chi, Aus, Fin, Fra, Jap, Spa, Swe, UK, and US when the first dummy variable was used; and in Chi, Aus, Bel, Can, Fin, Fra, Ita, Jap, Swe, UK, and the US when the second dummy

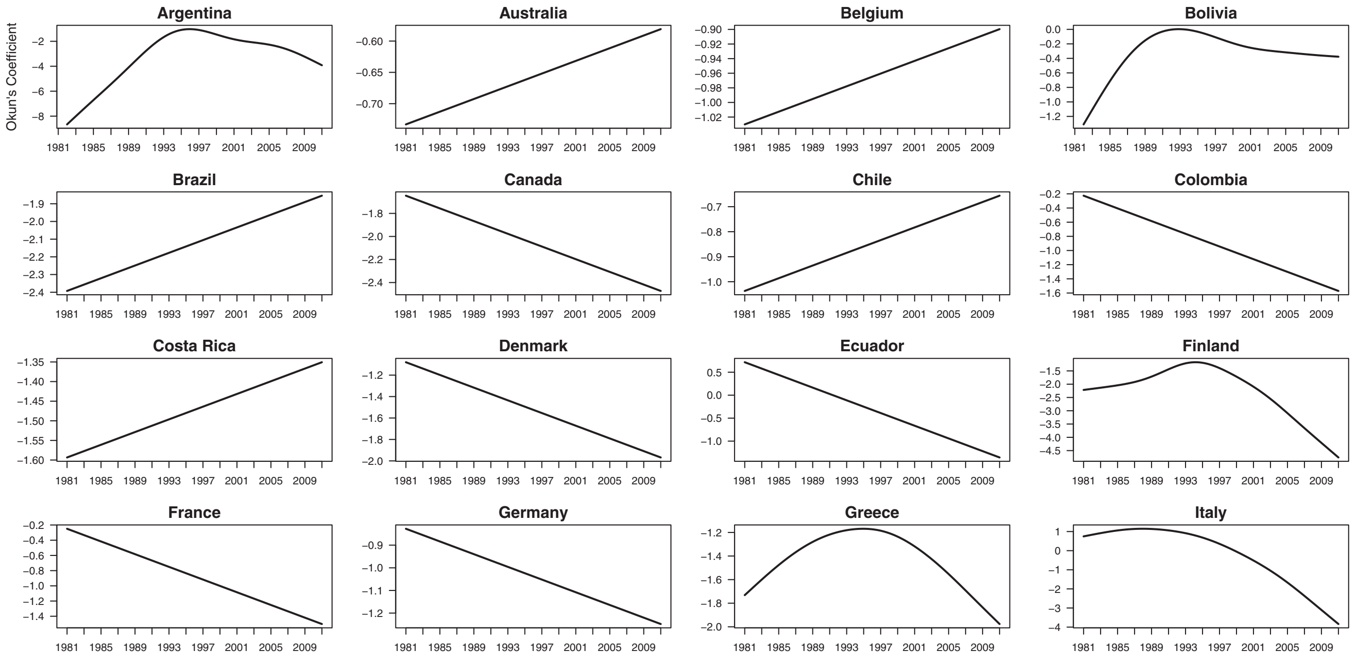

FIGURE 1. Time-varying Okun coefficients (first 16 countries).

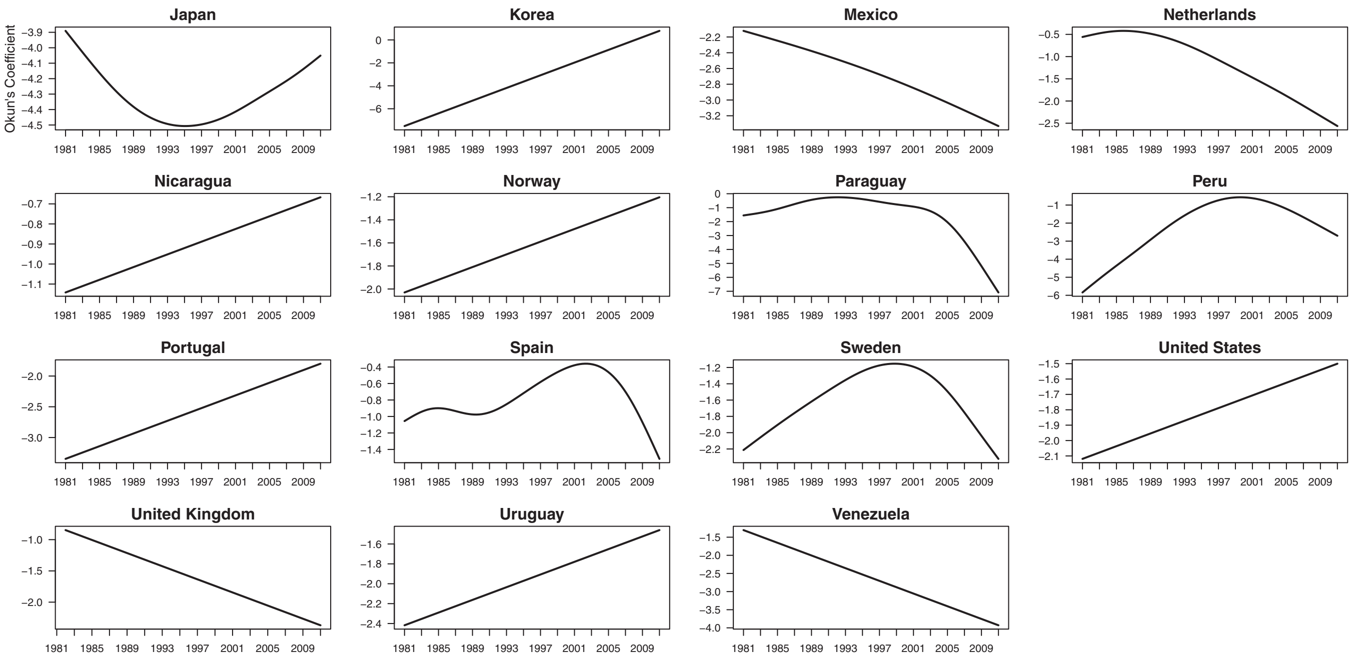

FIGURE 2. Time-varying Okun coefficients (last 15 countries).

TABLE 2. Potential rate 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

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

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TABLE 3. Estimates of models (3) and (4) using the first dummy variable: $D_t = 1$ if $g_t > g_n$

	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

TABLE 3. Continued.

	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
					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	0.558	3.294**	0.69	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

[a]CDP included as additional regressor.
[b]Imposing the CDP with unit coefficient.
^,*, ** Statistical significance at the 10%, 5%, and 1% level.

TABLE 4. Estimates of models (3) and (4) using the second dummy variable: $D_t = 1$ if $g_{3\text{MA},t} > g_{\text{AVE},t}$

	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

TABLE 4. Continued.

	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
					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

[a]CDP included as additional regressor.
[b]Imposing the CDP with unit coefficient.
^,*, ** Statistical significance at the 10%, 5%, and 1% level.

variable was used. These instruments seem to be valid according to the test of overidentifying restrictions.

Nevertheless, the 2SLS estimation results are subject to the problem of weak identification, the only exception being Fin when estimation using the first dummy variable was carried out.[29] Therefore, with the exception of Fin (where we used standard 2SLS), we employed again Fuller (1977)'s LIML with $a = 1$ to estimate model (3) using IV methods. These estimates satisfy the diagnostic tests (at the 10% level of significance), with the following exceptions: (1) autocorrelation problems were found in Bel when the second dummy variable was used, so that we employed Newey–West standard errors in this case (using two lags in the autocorrelation structure); and (2) normality problems were found in Chi, Aus, Fin, Fra, Jap, and UK when the first dummy variable was used and in Fra, Ita, Jap, and UK when the second dummy variable was used.

However, in Tables 3 and 4 we have decided to report the OLS estimation results because they provide a more appropriate benchmark to compare the results obtained from different estimators.[30]

The OLS results do not present problems of autocorrelation. However, some countries presented normality problems (CR, Nic, Par, Den, Fin, Ger, Ita, and Neth in Table 3; and CR, Nic, Fin, Ger, Ita, and Neth in Table 4) and correct functional form problems (Col, Fin, Ita, and US in Table 3 and Den and US in Table 4).

On the other hand, the PRS estimates of model (4) presented in Tables 3 and 4 do not seem to present autocorrelation problems. With respect to the results presented in Table 3, normality problems were found in CR, Nic, Aus, Bel, Ger, and Neth; and correct functional form problems were found in Col, Aus, Den, Fin, and UK. Regarding the estimates presented in Table 4, normality problems were found in CR, Nic, Ger, and Neth, whereas correct functional form problems were found only in UK.

Finally, regarding the AMG estimation of model (3), the first dummy variables introduced were constructed using the panel estimates of g_n (that is, 2.20 and 2.49 for the AMG[1] and AMG[2] estimation, respectively), whereas the second dummy was built with respect to the average g_t for all countries (that is, 2.67).

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 3.1. This table shows that the g_n^{H}s and g_n^{L}s obtained from 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^{H}s, whereas not all countries present statistically significant g_n^{L}s. The latter is particularly relevant to LA countries, because the only countries that presented statistically significant g_n^{L}s were Chi, Col, CR, Ecu, and Mex. Regarding the sample of OECD countries, Fin and Gre were the only two countries in which the respective g_n^{L}s were found to be statistically nonsignificant in the majority of the estimates.

Our findings corroborate the results presented by Haltmaier (2012), who also finds differences of the effects of recessions in a sample of advanced and emerging countries. Her panel regressions show that the characteristics of recessions (depth, length, and extent) are important to explain the cumulative four-year loss in the level of potential output following an output break preceding a recession. Specifically, she finds that (1) the depth of the recession is important for advanced economies, but not the length, whereas the opposite is true for emerging markets, and (2) the output loss is on the average larger for the advanced than for the emerging economies.[31]

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, $g_n^{\mathrm{L}} - g_n$ can be considered a measure of the output gap in low-growth periods, whereas $g_n^{\mathrm{H}} - g_n$ can be regarded as a measure of the output gap in high-growth periods. The estimated output gaps for the respective countries are all similar and show the robustness of the results obtained.

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

5. CONCLUDING REMARKS

The present article is related to the different postwar empirical studies that have dealt with the interaction between short-run business cycle fluctuations and long-run 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 of business cycles on the latter in a sample of 13 Latin American and 18 OECD countries during the period 1981–2011.

Using OLS/IV estimates, a panel estimator that takes into account parameter heterogeneity and cross-section dependence, and a nonparametric 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 interesting differences between countries, because less than half of the sample of Latin American countries (only 5 out of 13 countries) experienced statistically significant changes of this measure of potential output in periods of low growth, whereas the majority of OECD countries (16 out of 18 countries) experienced statistically significant changes of the measure of potential output in low growth

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

TABLE 5. Continued.

	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
								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	—	0.71	0.80	0.87	1.18	0.79	0.71	1.18	3.29	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

[a]CDP included as additional regressor.
[c]Imposing the CDP with unit coefficient.
— The estimate is not reported because it was found to be statistically nonsignificant (see Tables 3 and 4).

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

	Low-growth periods: $g_n^{\mathrm{L}} - g_n$									High-growth periods: $g_n^{\mathrm{H}} - g_n$								
	First dummy				Second dummy					First dummy				Second dummy				
	OLS	AMG[1][a]	AMG[2][b]	PRS	OLS	AMG[1][a]	AMG[2][b]	PRS	**Average**	OLS	AMG[1][a]	AMG[2][b]	PRS	OLS	AMG[1][a]	AMG[2][b]	PRS	**Average**
									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**

TABLE 6. Continued.

	Low-growth periods: $g_n^L - g_n$									High-growth periods: $g_n^H - g_n$								
	First dummy				Second dummy					First dummy				Second dummy				
	OLS	AMG[1][a]	AMG[2][b]	PRS	OLS	AMG[1][a]	AMG[2][b]	PRS	**Average**	OLS	AMG[1][a]	AMG[2][b]	PRS	OLS	AMG[1][a]	AMG[2][b]	PRS	**Average**
									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	—	−1.66	−1.09	−1.59	−0.59	−1.58	−1.18	−1.28	**−1.28**	1.52	1.83	2.79	1.99	2.77	2.25	2.75	2.07	**2.25**
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**

[a]CDP included as additional regressor.
[b]Imposing the CDP with unit coefficient.
— The estimate is not reported because it was found to be statistically nonsignificant (see Table 5).

periods. The latter is particularly important for 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 different models and techniques that could offer a more detailed analysis of the particular mechanisms that play a role in each country. Thus, a potentially fruitful line for future research could try to identify the relevant types of non-neutrality in each country using, for example, long-run non-neutral Blanchard–Quah decompositions as in Keating (2013) and trend-cycle decomposition models that incorporate the possibility of regime switches as in Guérin et al. (2015). Micro level studies exploring different mechanisms relating recessions and expansions to productivity are also relevant to distinguish the impact of business cycles on the level and on the long-run rate of growth. One possibility for achieving the latter might be to use stochastic frontier analysis as in Christopoulos and León-Ledesma (2014).

NOTES

1. This shortfall is a consequence of the financial stringency of the crisis and of the rational decision of the firms that avoid building out capacity rapidly because they already possess substantial slack.

2. To the best of our knowledge, Thirlwall (1969) 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 [Harrod (1939, 1960, 1970)]. Harrod defined 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" [Harrod (1939, 30)]. Hence, in Harrod's view, g_n represents the "economic optimum growth rate" [Harrod (1970, 737)], or the "welfare optimum in which resources are fully employed and the best available technology used" [Harrod (1960, 279)].

3. Thirlwall (1969) also suggested reversing the dependent and independent variables in the traditional Okun's law specification in order to avoid estimation biases caused by labor hoarding.

4. Knotek (2007) and IMF (2010) have used a dynamic version of Okun's law 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 nonsignificant variables according to the general-to-specific modeling approach. However, we do not report these results, because the main conclusions remained unaltered (results are available on request). More importantly, the use of lags of the dependent variable (g_t) in models (1) and (2) introduces further complications in a time-series setting because these variables are only weakly exogenous, and therefore its inclusion violates the exogeneity assumption of the estimators (see Section 3.2).

5. Thus, we have only considered the possibility of a time-varying Okun coefficient on unemployment in models (2) to (4). The possibility of a time-varying intercept (that is, a time-varying g_n) requires the use of different econometric techniques, and therefore we leave this topic for future research.

6. However, it was not possible to use bootstrapped standard errors in the panel estimations of model (4) because of an insufficient number of observations.

7. Given that both the panel and the PRS estimators are very recent econometric techniques, the use of IV methods in these estimators is a topic under construction. Recently, Chudick and Pesaran (2013b) have extended only the common correlated effects mean group estimator by allowing the inclusion of lagged values of the dependent variable (weakly exogenous regressors) in the panel data

model. On the other hand, regarding the PRS estimator, Marra and Radice (2011) propose a two-stage procedure for IV estimation when dealing with general additive models represented using any PRS approach and a Bayesian interval correction procedure; whereas Wiesenfarth et al. (2014) propose a Bayesian nonparametric IV approach based on Markov chain Monte Carlo simulation techniques under additive separability that corrects for endogeneity bias in regression models where the covariate effects enter with unknown functional form. Given that not all IV assumptions can be tested empirically, the implementation of these techniques is complicated, and therefore its use is left for future research.

8. The full report is available on request.

9. Also, like the C-statistic, the estimated covariance matrix used guarantees a non-negative test statistic [Baum et al. (2003, 2007)].

10. Thus, like the Hausman test, the C-statistic type test of endogeneity is formed by choosing OLS as the efficient estimator and the IV estimator as the inefficient but consistent estimator and, under conditional homoskedasticity, the two tests are numerically equal.

11. Under the assumption of conditional homoskedasticity, Hansen's J-statistic becomes the well-known Sargan statistic of overidentifying restrictions.

12. The results obtained from the C-statistic type test of endogeneity and from the test of overidentifying restrictions using the different combinations of instruments are not reported here in order to discuss only the relevant results, but they are available from the author on request.

13. Again, we only discuss the most important results in each section; however, a detailed report showing all the results obtained is available on request.

14. Between the pooled and the MG estimator, it is possible to find the pooled mean group (PMG) estimator developed by Pesaran and Smith (1999). This approach combines pooling and averaging because 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 used because no long-run slope coefficient were included.

15. 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 [Pesaran (2004); Chudick and Pesaran (2013a)].

16. Pesaran (2006) 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 with 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 (2006) show that this assumption does not affect its performance.

17. The Monte Carlo simulations reported by Bond and Eberhardt (2013) 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.

18. Bond and Eberhardt (2013) and Eberhardt and Teal (2014) explain that the c_t coefficients are extracted from the regression in first differences because nonstationary variables and unobservable common factors are believed to bias the estimates in the regressions in levels. We have decided to perform the original AMG estimation notwithstanding we have a model in first differences, because the sole interest is to analyze if the estimates of g_n^{H} and g_n^{L} differ from the original estimate of g_n.

19. 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.

20. Thin plate regression splines are low-rank isotropic smoothers because they approximate well the behavior of a full-rank thin plate spline. Their use possesses some specific advantages such as convenient mathematical properties, reasonably good computational efficiency, and avoiding the need to choose knot locations [Wood (2003, 2006); Marra and Radice (2010)].

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

22. Note that, for the case of a single endogenous regressor, the Cragg–Donald F-statistic is simply the first-stage F-statistic [Stock and Yogo (2005)]. 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 [Stock et al. (2002); Baum et al. (2007)]. The only country that satisfied this condition was Fin.

23. In general, the results obtained from models (1) and (3) using other estimators such as the LIML and the Fuller estimator with $a = 4$ were fairly similar to the ones here reported.

24. The null hypothesis was also strongly rejected when the CD test was applied to the individual g_t and Δu_t series. The value for 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).

25. The edf of the smooth term coefficients on g_{t-1} are above 1 in all cases (Arg = 1.96; Bol = 3.50; UK = 1.41), and the p-values associated with these estimated smooth functions are all smaller than 0.05. The edf of the smooth term coefficient on Δu_{t-1} for UK is 1 (p-value = 0).

26. Note that the time-varying coefficients obtained in our study represent Okun coefficients on unemployment, whereas the ones found by Zanin and Marra (2012) represent time-varying Okun coefficients on output. Hence, strictly speaking, it is not possible to establish a direct comparison between the results.

27. The complete estimates are available on request.

28. Therefore, these IV estimations were carried out only in the countries in which the null hypothesis of the C-test of endogeneity was rejected when model (1) was estimated (that is, Arg, Bra, Chi, Ecu, Nic, Par, Peru, Uru, Aus, Bel, Can, Fin, Fra, Ita, Jap, Kor, Neth, Nor, Spa, Swe, UK, and US).

29. Similarly, the null hypothesis of Anderson (1951)'s LM underidentification test was rejected only in this case.

30. First, the IV estimates of model (3) do not alter the main conclusions of the paper (results are available on request). Second, the use of generated regressors in an IV context requires the implementation of bootstrap testing procedures, which were not used because we have only employed bootstrap estimation methods. This is because we have sampled a set of observations with replacement (that is, the generated dummy variables) to estimate model (3). Efron and Tibshirani (1994) and Davison and Hinkley (1997) provide some ideas on how to carry out bootstrap testing procedures.

31. Calderón and Fuentes (2014) also found different effects of the cost of recessions (measured by either amplitude or cumulative loss) on actual output between industrial and emerging countries. They compare the preglobalization (1970–1984) and globalization (1985–2007) periods, finding that (1) during the globalization period, recessions are less severe for LA and the Caribbean than in the previous period; (2) recoveries are swifter and stronger amongst emerging countries, partly because of stronger rebound effects or to the fact that these countries have experienced a larger trend-growth rate than industrial economies.

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APPENDIX A: DERIVATION OF EQUATION (15)

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

$$\int [s^2(t,\boldsymbol{\delta})]^2\,dt = \int \left[\frac{\partial^2 s(t,\boldsymbol{\delta})}{\partial (t,\boldsymbol{\delta})^2}\right]^2 dt \tag{A.1}$$

$$= \int \left[\frac{\partial^2 \sum_{k=1}^{q} \delta_k b_k(t)}{\partial (t,\boldsymbol{\delta})^2}\right]^2 dt \tag{A.2}$$

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$$= \int \left[\delta^{\mathbf{T}}\mathbf{b}(\mathbf{t})\right]^2 dt \quad \textbf{(A.3)}$$

$$= \int \left[\delta^{\mathbf{T}}\mathbf{b}(\mathbf{t})\mathbf{b}(\mathbf{t})^{\mathrm{T}}\delta\right] dt \quad \textbf{(A.4)}$$

$$= \delta^{\mathbf{T}}\left(\int \left[\mathbf{b}(\mathbf{t})\mathbf{b}(\mathbf{t})^{\mathrm{T}}\right] dt\right)\delta \quad \textbf{(A.5)}$$

$$= \delta^{\mathbf{T}}\mathbf{S}\delta. \quad \textbf{(A.6)}$$

This is the result shown in equation (15).

APPENDIX B: 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