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The Natural Rate of Unemployment in Brazil, Chile, Colombia and Venezuela: some results and challenges[*]

Tito Nícias Teixeira da Silva Filho[**]

Abstract

This paper summarises the research results obtained by the group of central banks (Brazil, Chile, Colombia and Venezuela) that joined the research program on the Natural Rate of Unemployment – under the coordination of the Central Bank of Brazil – within the Joint Investigation on Non Observable Variables Project, and whose final results were presented at the XII Meeting of the Network of America Central Bank Researchers (CEMLA) held at Madrid in November 2007. The evidence obtained shows that the natural rate of unemployment is estimated with great uncertainty: besides sizable parameter uncertainty, estimates are very sensitive to the particular method used. This marked imprecision reflects the difficulties and challenges involved in the natural rate's estimation. Nonetheless, the research also shows that there seems to be much room available for improvement, especially those stemming from a more careful modelling process and better care with the data, particularly regarding supply shocks proxies, given their importance in inflation dynamics. Indeed, this "channel" seems to be the most promising one to both narrow down the uncertainty about the NAIRU and improve the reliability of inferences.

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1 – Introduction

This paper summarises the research results obtained by the group of central banks [see da Silva Filho (2008) for Brazil, Restrepo (2008) for Chile, Arango *et al.* (2007) for Colombia and Bujanda (2008) for Venezuela] that joined the research program on the Natural Rate of Unemployment – under the coordination of the Central Bank of Brazil – within the project "Investigación Conjunta Sobre Variables No Observables" (Joint Investigation on Non Observable Variables), and whose final results were presented at the "XII Reunión de la Red de Investigadores de Bancos Centrales del Continente Americano (CEMLA)" (XII Meeting of the Network of America Central Bank Researchers) held at Madrid in November 2007.[1] The project proved to be highly beneficial to all participants not only due to the exchange of valuable experiences and ideas between the central banks, but also for being a catalyst for starting or deepening the research about the natural rate of unemployment within each central bank.

The project also included joint investigation on three other non observable variables: potential output, the real equilibrium exchange rate and the natural rate of interest. Among the eleven central banks that joined the research project, the ones from Brazil, Chile, Colombia and Venezuela were the ones who joined the program on the natural rate of unemployment. The small number of participants in the natural rate of unemployment group – the smallest group – especially in relation to the large number of participants in the potential output group – the largest group – is the first issue to be called to attention. This "observable gap" is puzzling since one crucial input in potential output's estimation – at least in the production function method – is precisely the estimate of the natural rate of unemployment. This fact raises two possibilities: either the popular production function method was not widely used to calculate potential output – which was not actually the case – or some other simple, possibly mechanical, easily obtainable, natural rate estimation method was used. Indeed, the method used in those cases was the widely known HP filter. This state of affairs is worrisome, since the HP filter has important limitations and drawbacks. Indeed, as argues da Silva Filho (2008) "… the HP filter has frequently been much more of a curse than a solution to the profession, often preventing economists to delve into the subject at hand."

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[1] Evidently, the results are said to be "final" in the sense that the joint project formally ended in November 2007. However, all the research efforts certainly continue within each central bank.

Despite the apparent low interest on the natural rate of unemployment estimation (within the research project), it is hard to overstate its importance in macroeconomics, whether theoretically or empirically. For example, the natural rate plays a crucial role in two key macroeconomic concepts: money neutrality and potential output. Moreover, despite much controversy (see Stock and Watson (1999) and Atkeson and Ohanian (2001) for two opposing views), the Phillips Curve (PC) framework is considered by many economists a precious tool for predicting inflation. Blinder (1997), for example, has praised the reliability of the PC framework by stating that it is '[…] the "clean little secret" of macroeconometrics.' Also, thinking about the natural rate of unemployment force us to think about the labour market structure, and labour-market-related indicators such as wages and productivity.[2]

The paper is organised as follows: Section 2 defines the natural rate of unemployment and provides a brief analysis of the debate on whether or not the natural rate of unemployment and the NAIRU can be regarded as synonyms. Section 3 presents the methods that were used by each central bank participant in order to estimate the natural rate of unemployment for the respective countries. Section 4 summarizes the estimation results for each country and looks if there are empirical regularities between them from a labour market perspective. Section 5 provides a brief assessment on the approaches used and results obtained. Section 6 concludes the paper.

2 – The Natural of Unemployment

The difficulties surrounding the natural rate of unemployment estimation go far beyond the fact that not only is it a non observable variable but it is usually estimated very imprecisely (see Staiger *et al.*, 1996).[3] Actually, economists are not even able to agree on what it means and, thus, on the best estimation strategy. The concept of the natural rate of unemployment was proposed by Friedman (1968) who – inspired by

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[2] Of course, there are other methods to calculate potential output that do not use the natural rate of unemployment as an input (e.g. univariate methods). Similarly, besides the Phillips Curve, the literature lists other methods to calculate the natural rate of unemployment.

[3] In order to provide some idea on the degree of uncertainty surrounding NAIRU estimates, it is useful to mention the confidence intervals obtained by Staiger *et al.* (1996) for the US – which could be considered a lower bound for other countries. They found 95% confidence intervals for the NAIRU spanning almost four percentage points (3.9%–7.6%) when inflation was measured by the CPI and nearly two and a half points (4.5%–6.9%) when the core CPI was used instead. Moreover, note that the confidence intervals found in the literature (including Staiger *et al*., 1996) are based on parameter uncertainty only. If model uncertainty is also taken into consideration uncertainty will be even greater.

Wicksell's concept of the natural rate of interest – stated in his presidential address to the American Economic Association that "The natural rate of unemployment, in other words, is the level which would be ground out by the Walrasian system of general equilibrium equations, provided that there is embedded in them the actual structural characteristics of the labour and commodity markets, including market imperfections, stochastic variability in demands and supplies, the cost of gathering information about job vacancies and labour availabilities, the costs of mobility, and so on."[4]

Although (price or wage) inflation is not explicitly mentioned in this widely cited definition – which highlights the natural rate's structural determinants – it is straightforward to infer that whenever real wages (adjusted for productivity) are changing the labour market could not be in equilibrium. Indeed, the link (or its absence) between the (natural) rate of unemployment and inflation was made explicit by Friedman himself soon afterwards, as he stated "You will recognize the close similarity between this statement [the above definition] and the celebrated Phillips Curve. The similarity is not coincidental."[5] He then continued his speech so as to argue that in the long run the PC is vertical at the natural rate of unemployment. Hence, it is not surprising that many economists have been using the PC framework in order to estimate the natural rate of unemployment. While the PC emphasizes wage rigidities and inflation expectations, the above definition emphasizes the structural factors behind the unemployment, including imperfections and rigidities of other nature as well.

However, some economists [e.g. Tobin (1998) and King (1998)] argue that this approach does not provide estimates of the natural rate of unemployment, but rather estimates of the non-accelerating inflation rate of unemployment – the so-called NAIRU[6] – a concept created by Modigliani and Papademos (1975).[7] More recently a

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[4] The same concept was concomitantly developed by Phelps (1968), although he called it the steady-state equilibrium unemployment rate.

[5] Actually, when explaining the concept of the natural rate of unemployment Friedman also emphasized wage developments. Although this part of Friedman's explanation is usually ignored, he had just said that "At any moment in time, there is some level of unemployment which has the property that is consistent with equilibrium in the structure of *real* wage rates. At that level of unemployment, real wages are tending on the average to rise at a "normal" secular rate, i.e., at a rate that can be indefinitely maintained so long as capital formation, technological improvements, etc, remain on their long-run trends. A lower level of unemployment is an indication that there is an excess demand for labour that will produce upward pressure on real wage rates. A higher level of unemployment is an indication that there is an excess supply of labour that will produce downward pressure on real wage rates. The "natural rate of unemployment," in other words, is the level that would be grounded ..."

[6] Note that this acronym is a misnomer. The correct one would be the non-*increasing* inflation rate of unemployment (NIIRU). Another option could be non-accelerating *price level* of unemployment (NAPLU).

taxonomy for the NAIRU has been proposed (see Richardson *et al.*, 2000): the short-run NAIRU, the NAIRU and long-run equilibrium rate of unemployment (i.e. akin to the natural rate), which differ from each other according to the time frame they refer to and to what kind of shocks are considered. On the other hand, many economists do consider the concepts natural rate of unemployment and NAIRU as synonyms (e.g. Gordon, 1997; Staiger *et al.*, 1997; Stiglitz, 1997; Mankiw, 2001; Ball and Mankiw, 2002). Here as well both concepts are used interchangeably.

The major reason for that understating is that – in my point of view – when interpreted *literally*, the NAIRU not only could be misleading but is a poor guide for monetary policy. Several reasons concur for that. First, although the NAIRU concept focuses exclusively on (short run) inflation stability, agents read it as a structural labour market indicator, one which would reflect whether or not the labour market has some spare capacity available at any given moment. However, since it is perfectly possible to have, at the same time, the unemployment rate below the (literal) NAIRU and above its equilibrium level, the concept could be misleading. Such a situation – which is actually common – could arise due to adverse supply shocks, and would cause the wrong impression that the labour market is overheated when, in fact, it is not. Second, since inflation is likely to be volatile in the short and medium run, so will be the NAIRU. Therefore, the NAIRU is unlikely to provide a good operational guide for monetary policy. Indeed, a target that keeps moving cannot be seen as a useful benchmark, and could end up providing more noise than signal.

Third, policy advices based on the (literally interpreted) NAIRU framework – i.e. the policymaker counteracts any inflationary/deflationary episodes by changing the unemployment rate – not only will not be optimal but is likely to produce undesirable outcomes. For example, such a strategy will require frequent and large changes in the interest rate, which will generate excess volatility in unemployment and output, decreasing welfare. Moreover, if inflation increases because of adverse supply shocks, then the best monetary policy strategy advises not to react to the first round inflationary effects.[8] Also, given that opposite shocks might hit the economy within a short time interval, attempts to stabilise inflation might end up causing just the opposite result. Fourth, if the policymaker does want to stabilise inflation using the "literal NAIRU

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[7] Actually, they called it the non-*inflationary* rate of unemployment (NIRU), which is also inadequate since inflation need not be zero when unemployment coincides with its natural rate.
[8] Moreover, many economists consider that interest rate smoothing is an important feature of optimal monetary policy.

strategy" it probably won't be well succeeded, given that the lags on the transmission mechanism of monetary policy will prevent that.

Hence, the NAIRU would only be a useful and sensible guide for monetary policy as long as it is likely to reflect structural unemployment. In that case it would be a much more stable indicator, especially in the short-run. In other words, the NAIRU is useful only if it is *not* understood literally. Put differently, it is useful only as it moves towards the natural rate concept.[9] And how can be that accomplished? Basically, to a large extent, by taking into account those factors that could change the short-run trade off between inflation and unemployment (e.g. supply shocks).

This assessment has direct consequences on the way the NAIRU is (or should be) estimated, since those shocks must be included in the PC specification. As a matter of fact, they always must be taken into account, otherwise NAIRU estimates will be biased (and more volatile), unless the former are uncorrelated with unemployment, which is unlikely. Furthermore, by identifying and incorporating relevant shocks into the model – whether benign or adverse – one gets a better understanding of the inflation dynamics, enhancing transparency and communication. For example, it becomes easier for the central bank to explain increases in the interest rate in a scenario where the economy is operating below its potential. Similarly, if, say, there is an increase in trend productivity, the central bank can decrease interest rates allowing the unemployment rate to fall – at least for a while – below what is thought to be the natural rate. Indeed, such a situation reminds one of what occurred in the second half of the 1990s in the U.S.

However, one might still argue that even taking shocks into account PC-based NAIRU estimates are still unable to fully reflect structural unemployment, since the natural rate determinants are not explicitly modelled. This is probably right, but structural models are not a panacea as well. Not only is there no consensus about the best structural model to use, but many factors that are thought to affect the natural rate are very difficult to be accounted for, such as institutional features and policies. Hence, there is no guarantee that a structural approach will deliver clear superior results than the PC framework. Finally, even though the latter does not provide a framework that explicitly models the natural rate determinants, if supply shocks are successful accounted for, the resulting NAIRU estimate should provide a good approximation of

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[9] Note that the NAIRU concept converges to the natural rate concept if one thinks about it as the non-increasing *medium/long run* inflation rate of unemployment.

the structural unemployment.

Anyway, it should be pointed out from the outset that all central banks that joined the natural rate of unemployment research project used the PC framework intensively – although other methods were also used – which means that they ended up treating both concepts as synonyms.

3 – Methodologies

This section presents the methods that were used by the group of four central banks that joined the natural rate of unemployment project. Although they are not exhaustive, they encompass the main methods that have been used in the literature to estimate the natural rate of unemployment.

3.1 – Reduced Form Methods: The Phillips Curve-Based Framework

The most popular method for estimating the natural rate of unemployment is the Phillips Curve (PC) framework, which relates inflation to a measure of slackness in the economy, usually either the output gap or the unemployment gap. This framework – which despite its simplicity is very flexible – presents a very interesting balance between a-theoretical approaches, like purely statistical filters, and structural methods. Indeed, the Phillips Curve can be obtained as the reduced form of several types of structural models. It is not surprising, therefore, that it has been widely used by economists (e.g. Congressional Budget Office, 1994; Gordon, 1997; Staiger et al., 1996; Stock and Watson, 1997; Ball and Mankiw, 2002), and policymakers.[10]

In its general specification the Phillips Curve could be stated as

$$\Delta \pi_t = \alpha(L)\Delta \pi_{t-1} + \beta(L)\left(u_t - u_t^n\right) + \gamma(L)\mathbf{x_t} + \varepsilon_t, \quad \varepsilon_t \sim \mathrm{NID}\left(0, \sigma_\varepsilon^2\right) \quad (1)$$

where $\alpha(L), \beta(L)$ and $\gamma(L)$ are lag polynomials, $\pi_t = \Delta \ln CPI_t$, u_t is the (seasonally adjusted) unemployment rate, u_t^n is the unobservable (and possibly time-varying) natural rate of unemployment and $\mathbf{x_t}$ is a vector of other inflation determinants, among which supply shocks play a central role.

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[10] It is also the preferred method of the OECD.

Note that equation (1) implicitly assumes a vertical PC and random-walk expectations (i.e. $\pi_t^e = \pi_{t-1}$). Not only such an assumption has been widely used elsewhere (e.g. Gordon, 1997; Staiger et al., 1996; Stock and Watson, 1997; Ball and Mankiw, 2002), but random-walk inflation forecasts have proven to be a very tough benchmark to beat (e.g. Stock and Watson, 1999; Gavin & Mandal, 2003).

One particular case of interest is obviously the one in which the NAIRU is assumed to be constant. In that situation equation (1) simplifies to

$$\Delta\pi_t = c + \alpha(L)\Delta\pi_{t-1} + \beta(L)u_t + \gamma(L)\mathbf{x_t} + \varepsilon_t \qquad (2)$$

and the NAIRU could be easily estimated by OLS, since it is simply the (negative) ratio of the constant term to the sum of the coefficients on lagged unemployment (equation 3).

$$\bar{u} = -c/\beta(1) \qquad (3)$$

However, in such a case one difficulty comes from assessing how precise are NAIRU's estimates, given that it is a nonlinear function of regression coefficients. Two methods have been used for calculating uncertainty about the NAIRU. The first is the so-called Delta Method, which uses a first order Taylor series approximation to the non linear estimator (3) in order to derive its asymptotic variance. The second one is the so-called Gaussian Method, which uses the duality between hypothesis testing and confidence intervals to calculate the latter at any desired significance level.[11]

Before proceeding, it is important to note that any supply shock that enter the PC needs to be normalised so that it has a zero net effect on the NAIRU estimation, otherwise the estimate will be biased whenever the shock does not have a zero mean.

As mentioned before, one appealing feature of the PC framework is its flexibility. Indeed, it can be used, for example, together with the unobserved components (UC) technology when one wants to allow for the possibility of a time-varying NAIRU (TV-NAIRU). In this case instead of carrying out a non linear estimation of (1), one can express the model in state space form and estimate it by

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[11] For more details on the two procedures – and evidence on which one seems to be the best – see Staiger *et al.* (1996).

maximum likelihood using the Kalman Filter. One advantage of this approach is that the NAIRU can be allowed to vary without having to specify its determinants. Yet, one must specify a statistical model for the NAIRU.

One popular statistical assumption is that the NAIRU evolves according to a random walk. Equations (4) and (5) illustrate this approach using the random walk assumption. Note that if $\text{var}(\xi_t) = 0$ then the model (4)–(5) collapses into model (2)–(3).

$$\Delta\pi_t = \alpha(L)\Delta\pi_{t-1} + \beta(L)\left(u_t - u_t^n\right) + \gamma(L)\mathbf{x_t} + \varepsilon_t \qquad \varepsilon_t \sim NID\left(0, \sigma_\varepsilon^2\right) \qquad (4)$$

$$u_t^n = u_{t-1}^n + \xi_t \qquad\qquad\qquad \xi_t \sim NID\left(0, \sigma_\xi^2\right),\ E(\varepsilon_t, \xi_t) = 0 \qquad (5)$$

Other possibility for estimating a TV-NAIRU is to use the Ball and Mankiw (2002) approach, which is a two-step procedure that starts from a version of the PC without supply shocks, and that assumes a constant NAIRU. Equation (6) shows the resulting PC specification in this case (dynamics are ignored for simplicity):

$$\Delta\pi_t = \beta u^n - \beta u_t + \varepsilon_t \qquad (6)$$

which could be rewritten as

$$u^n + \frac{\varepsilon_t}{\beta} = u_t + \frac{\Delta\pi_t}{\beta} \qquad (7)$$

Note that while the l.h.s. of (7) is non observable – since it contains the NAIRU – the r.h.s. could be used as an estimate, since it can be calculated from the available data on unemployment and inflation (given the OLS estimate of β). Then, in the second step an HP filter – see equation (10) – is applied to the r.h.s. in order to extract the underlying trend, which is considered to reflect the NAIRU.

Another possibility for estimating a TV-NAIRU within the PC framework is to use a spline as the statistical model for the NAIRU. In such a setting the NAIRU is assumed to vary slowly over time. Similarly to the B&M method, this method can be easily implemented through OLS estimation. In this case the PC could be stated as

$$\Delta \pi_t = \phi' S_t + \alpha(L)\Delta \pi_{t-1} + \beta(L)u_t + \gamma(L)\mathbf{x_t} + \varepsilon_t \qquad (8)$$

$$u_t^n = -\phi' S_t / \beta(L) \qquad (9)$$

where $\phi' = -\beta(L)\overline{\phi}'$, $u_t^n = \overline{\phi}' S_t$ and S_t is a vector of deterministic functions of time. Usually a cubic spline is assumed.[12]

Yet, another possibility for calculating a TV-NAIRU using the PC framework is to take into account demographic and structural changes in the labour force. For example, in a situation in which the share of young workers – which are more inexperienced and have a higher job turnover rate – in the labour force is increasing over time, not only the unemployment rate is expected to rise but the natural rate of unemployment is likely to increase as well. The same phenomenon happened in several countries in recent decades as women began to join the labour force. More generally, whenever the relative share of labour force groups change the natural rate of unemployment is also likely to change. Consequently, this approach tries to estimate (possibly different) natural unemployment rates for different labour force groups – whether divided by gender, race, experience, qualifications, etc – and then aggregate them so as to obtain an estimate of the overall natural rate of unemployment.

In order to implement this strategy a reference group is elected – usually the most employable group, i.e. the one with the lowest and most stable unemployment rates – and its natural rate is calculated using the PC method, assuming that within each group it remains constant.[13] Subsequently, all the other groups' natural rates are estimated based on regressions relating the reference group unemployment rate to each group's unemployment rate. Finally, the disaggregated natural rates are weighted by their respective labour force group shares so as to come up with an estimate of the aggregated natural rate.[14]

Note that all the above methods estimate the NAIRU taking explicitly into account the link between inflation and unemployment. Moreover, as mentioned above, despite its simplicity, the Phillips curve has a clear theoretical content, being a reduced

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[12] In the two knots case $S_t = \begin{bmatrix} \beta_0 & t & t^2 & t^3 & D_1(t-t_1)^3 & D_2(t-t_2)^3 \end{bmatrix}$, where $\begin{aligned} D_1 &= 0 \quad \text{if} \quad t < t_1 \\ D_1 &= 1 \quad \text{if} \quad t \geq t_1 \end{aligned}$ and $\begin{aligned} D_2 &= 0 \quad \text{if} \quad t < t_2 \\ D_2 &= 1 \quad \text{if} \quad t \geq t_2 \end{aligned}$.

[13] Hence, note that even assuming constant natural unemployment rates within each group, the overall natural rate can change due to changes in the composition of the labour force.

[14] For an example of this approach see Weiner (1993).

form compatible with several structural methods.

3.2 – Univariate Methods

Univariate methods aim at obtaining NAIRU estimates by focusing exclusively on the unemployment series. That is, neither inflation nor any other information besides the unemployment series itself is used. The key assumption behind those methods is that the unemployment trend can be read as the potential level of the variable. The disagreement lies precisely on what is considered being part of the trend and what it is not.

Among the main univariate methods there are the so-called filters. Filters have been extensively used to extract "potential" levels of economic variables. There are many options available in the literature like the Kalman Filter, the Baxter and King Filter, the Beveridge and Nelson decomposition, etc. Among those filters, the one that has been most widely used, due mainly to its simplicity, is the Hodrick-Prescott filter, which is given by the following minimization problem.

$$\min_{\{u_t^n\}_{t=1}^T}\left\{\sum_{t=1}^T\left(\ln u_t - \ln u_t^n\right)^2 + \lambda\sum_{t=2}^{T-1}\left[\left(\ln u_{t+1}^n - \ln u_t^n\right) - \left(\ln u_t^n - \ln u_{t-1}^n\right)\right]^2\right\} \qquad (10)$$

Note that while the first term tries to maximise the fit (i.e. the maximum fit would mean that the variable and the trend coincide) the second tries to maximise the smoothness of the trend (or, in other words, impose a penalty for the goodness of the fit). The lambda parameter gives the size of the volatility penalty. Hence if lambda is large enough the resulting series will be a linear trend, while if the penalty is zero the trend and the series will be indistinguishable.[15]

3.3 – Other Methods

Two other methods that have been used in the literature in order to estimate the natural rate of unemployment are the (multivariate) unobserved components method –

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[15] Note that some of those filters also have their multivariate version as, for example, the multivariate HP filter.

estimated with the Kalman Filter – and the structural VAR (SVAR).[16] The rationale is the same: both methods aim at separating the trend – the permanent component – from the cycle – the transitory component, but now with the help of other variables.

4 – Country Results

This section summarizes the natural rate estimation results for each country involved in the research project [see da Silva Filho (2008) for Brazil, Restrepo (2008) for Chile, Arango *et al.* (2007) for Colombia and Bujanda (2008) for Venezuela]. It also takes a brief look on whether there have been any empirical regularities between those countries according to labour market developments.[17] Although the actual estimation sample differs in each case (see Table 2), in order to provide a clearer outlook, Figure 1 plots the four countries' unemployment rates from 1986.1 to 2007.1.[18]

Figure 1
Quarterly Unemployment Rates
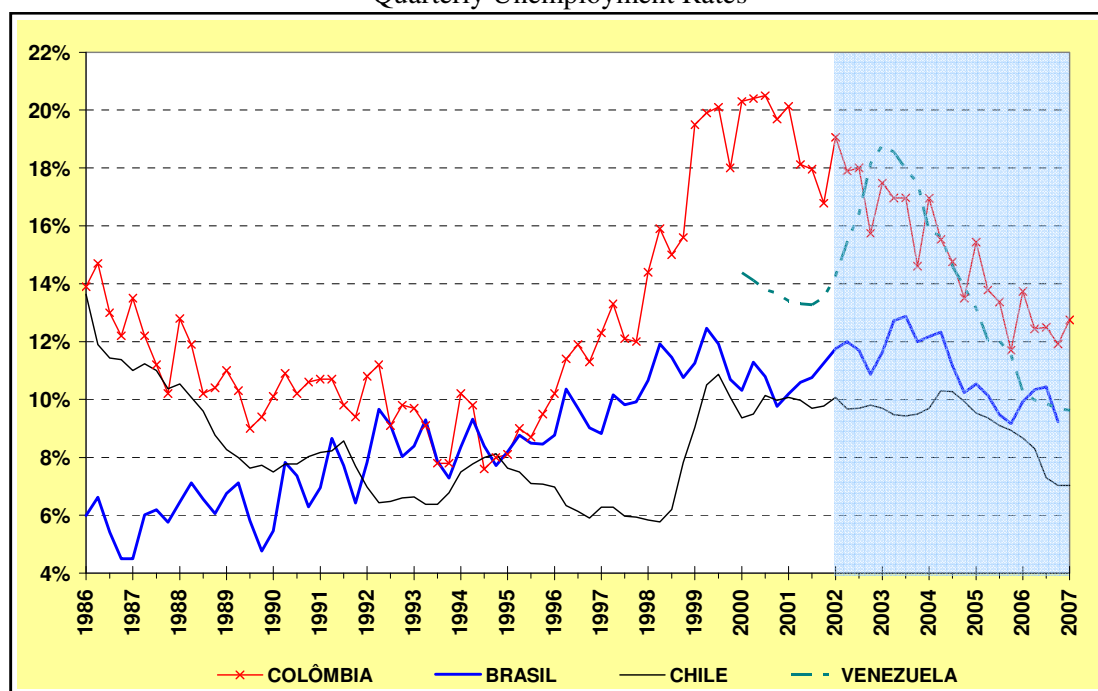
According to Figure 1, business cycles do not seem to have been much synchronised among BCCV during the period under analysis, except in the most recent years. While unemployment fell for almost ten years – until mid-1990s – in Chile and

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[16] For detailed expositions on the UC method and structural VARs see Kim and Nelson (1999) and Lütkepohl (2005), respectively.

[17] For conciseness, the four countries above will be referred to as BCCV.

[18] Except for Venezuela, where the unemployment data is available only from 2000.1 onwards.

Colombia, it increased for at least twelve years in Brazil, until 1999. Moreover, around mid-1995 there was a sharp reversal in the unemployment trend in Colombia, when it began to rise very rapidly, while Chilean unemployment continued to decrease until mid-1998, after a short-lived increase in 1994–95. Then, following the Russian crisis, Chilean unemployment soared, increasing by more than five percentage points in just one year, and remained close to its peak level for around six years. In its turn, unemployment in Colombia – which had already begun to increase around 1995 – soared too after the Russian crisis, and increased eight percentage points in just a two-year interval (1998–99).[19] However, note that since 2002/2003 BCCV's business cycles seem to have been well synchronised, as unemployment rates have begun to fall steadily in all four countries. Table 1 provides the associated correlations for the whole sample and for the most recent period.

Table 1
Unemployment: Annual Correlations (1986 – 2006)[a]

	Brazil	**Chile**	**Colombia**	**Venezuela**
Brazil	1	0.67	0.86	0.95
Chile	-0.06	1	0.75	0.78
Colombia	0.69	0.52	1	0.90
Venezuela[b]	0.94	0.69	0.49	1

(a) The shaded area shows correlations for the 2002–2006 period.
(b) Correlations from 2000 onwards.

As can be seen, the correlation coefficients are not very large when the full sample is considered. Indeed, there is no correlation between Brazilian and Chilean unemployment over the entire sample, although there is a positive correlation between Brazil and Colombia. In its turn, the correlation between the Chilean and Colombian unemployment rates is also positive, although much weaker. However, when the most recent period (2002–2006) is considered, the evidence points to a more uniform pattern. The correlation between Brazil and Chile changes from being slightly negative to positive, with a coefficient equal to 0.67. Moreover, the correlations between Brazil and Colombia and Chile and Colombia increase from 0.69 to 0.86 and 0.52 to 0.75, respectively. Despite being high, the comparisons with respect to Venezuela should be looked at with caution since the Venezuelan sample is short.

Table 2 provides – for each country's estimation sample – a few statistics on unemployment and inflation rates. Any inference should be taken cautiously, given the

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[19] For more details on the reasons behind the dynamics of unemployment in each country see the respective country papers.

likely methodological discrepancies in unemployment surveys and the different samples involved. Even so, Table 2 does suggest some interesting evidence. For example, the unemployment rate peak was extremely high in both Colombia and Venezuela, where one in every five people in the labour force was once unemployment, and much lower in Brazil and Chile. It is unlikely that methodological differences alone could explain such a discrepancy. On the other hand, minimum unemployment rates have been surprisingly close to each other, which means that the largest variation in unemployment rates took place in Colombia and Venezuela, while in Brazil and Chile it has fluctuated within a much narrower range.[20] One interesting question at this point would be whether (and to what extent) the larger variation in the first two countries reflects a more flexible labour market.

Table 2
Country Statistics

	Brazil	**Chile**	**Colombia**	**Venezuela**
Unemploy-ment	Min. = 8.8%	Min = 7%	Min. = 6%	Min. = 8%
	Mean = 10.5%	Mean = 8.6%	Mean = 13.2%	Mean = 13.8%
	Max. =12.9%	Max. = 14%	Max. ≈ 20%	Max. ≈ 20%
	Range = 4.1 pp	Range = 7.0 pp	Range ≈ 14.0 pp	Range ≈ 12.0 pp
Inflation[a]	Min. = 1.7%	Min = -0.8%	Min. = 3.9%	Min. = 10.4%
	Mean = 7.3%	Mean = 8.8%	Mean = 17.6%	Mean = 19.0%
	Max. =16.6%	Max. = 29.2%	Max. = 32.3%	Max. = 38.7%
	Range = 3.9 pp	Range = 30.0 pp	Range = 28.4 pp	Range = 28.3 pp
Frequency	Quarterly	Quarterly	Quarterly	Monthly
Sample	1996.2 – 2006.4	1987.3 – 2006.4	1985.2 – 2005.4	2000.8 – 2007.6
Obs.	43	78	83	83

(a) Twelve months inflation rates.

Although it is not possible to infer the dynamics of inflation from Table 2, Figure 2 shows that there has been a gradual disinflation process in all four countries, even though its pace and persistence has varied somewhat.[21] It is interesting to note that while in both Brazil and Venezuela the disinflation process experienced an important setback in early 2000s that fact did not occur in Chile and Colombia. Quite on contrary, there was a sharp disinflation in Colombia at the end of the 1990s, and inflation continued its downward path in Chile during that period.

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[20] Note, however, that if one considers the whole sample used in Figure 1, then Brazil would have had the lowest unemployment rate, and the smallest variation would go to Chile (around 9 p.p. and 7 p.p., respectively)

[21] Disinflation has taken place since early 1990s in Chile and Colombia, and since mid-1994 and mid-1996 for Brazil and Venezuela, respectively (the last two cases are not completely shown in Figure 2.

Figure 2
Monthly (Year-Over-Year) Inflation Rates[a]
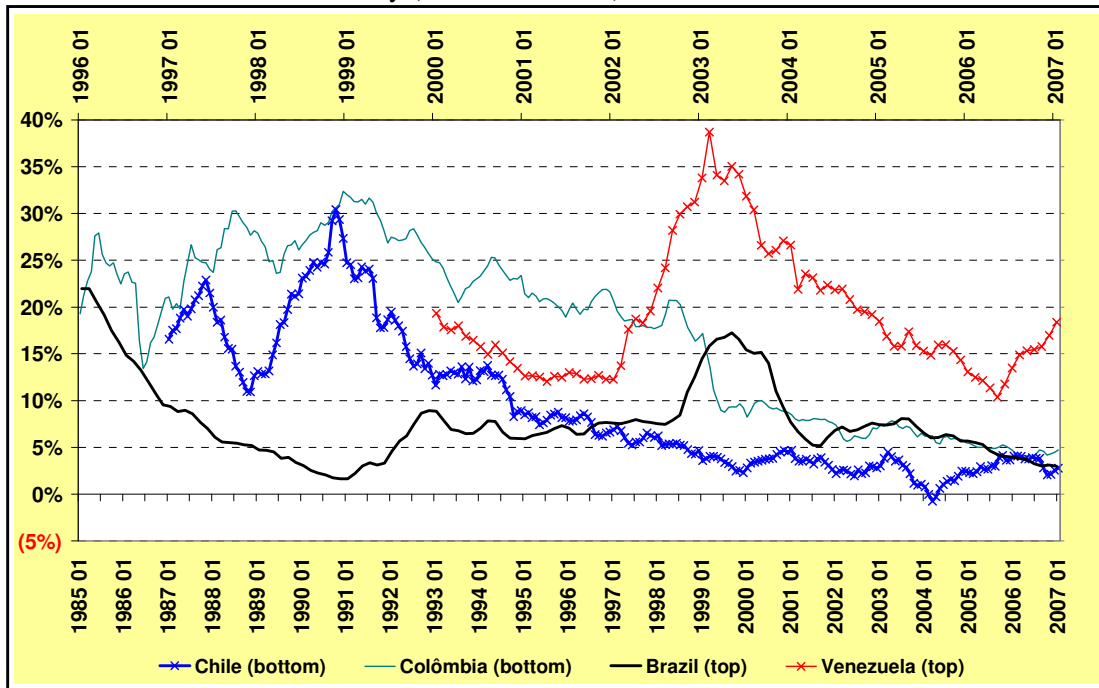
(a) The samples differ since they are based on actual estimation samples (see Table 2).

Figure 3
Changes in Annual Inflation and One-Period Lagged Unemployment

$$DInflBr = -24.23 + 2.135*UnBr\_1$$
$$(SE) \quad (12.4) \quad (1.16)$$

$$DInfCh = -5.606 + 0.5659*UnCh\_1$$
$$(SE) \quad (4.97) \quad (0.567)$$

$$DInfCol = 0.06531 - 0.0674*UnCol\_1$$
$$(SE) \quad (2.81) \quad (0.206)$$

$$DInfVen = 43.53 - 2.901*UnVen\_1$$
$$(SE) \quad (26.1) \quad (1.75)$$
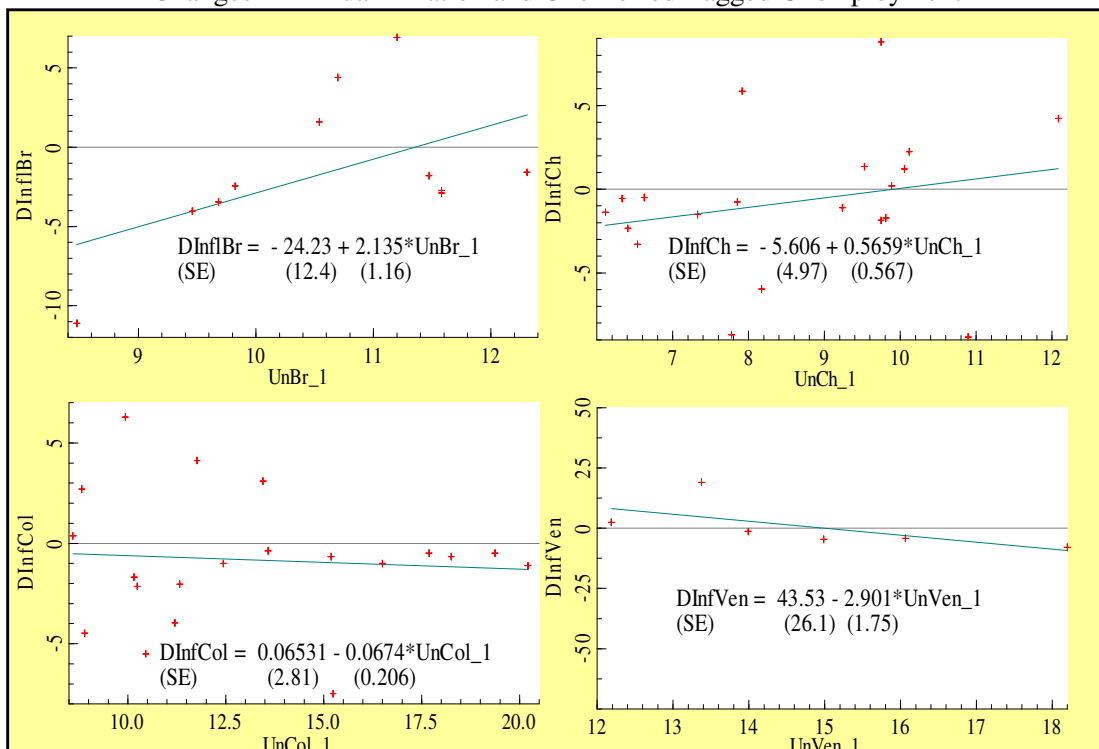
Figure 3 shows the relation between annual changes in inflation and unemployment lagged one period, for each country's estimation sample. Note that despite having the correct theoretical sign, the slope is virtually zero for both Venezuela

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and Colombia. Hence, there apparently is no trade off between inflation and unemployment in those countries. Moreover, based on this simple exercise, the Colombian data would imply a negative NAIRU. More surprisingly, for both Brazil and Chile the regression line has a positive slope, even though the link is not statistically significant at conventional significance levels.

That evidence strongly suggests that supply shocks must have been a key factor in explaining inflation dynamics in those countries, especially in Brazil and Chile. Indeed, the pivotal importance of supply shocks for the Brazilian inflation was pointed out by da Silva Filho (2008). Interestingly, the positive slope found for Chile was not shown in Restrepo's (2008) paper. That could be due to the fact that he plotted the difference between inflation and its trend – measured by the HP filter – against the unemployment gap (and not the first difference of inflation against the unemployment rate). Supply shocks were also claimed to be behind the very flat curve for Venezuela, according to Bujanda (2008). The evidence so far – especially the positive slope – suggests that estimating the NAIRU for BCCV is not an easy task. It also implies that identifying and measuring properly supply shocks are central to the success of the estimations.

Indeed, three out of the four countries above included supply shocks in the Phillips Curve (see the Appendix for a summary of each paper). Unexpectedly, Arango *et al.* (2007) did not take any supply shocks into account when estimating the NAIRU for Colombia, even though the correlation between inflation and unemployment for the so-called "basic unemployment group" was positive in two of the four sub-periods analysed. On the other hand, a major issue in da Silva Filho's (2008) paper was how to build good supply shocks for Brazil. One common finding among the papers that used supply shocks was the importance of exchange rate shocks in inflation dynamics, although they were only borderline significant in the Chilean case (when the whole sample was considered). In the Brazilian case, exchange rate effects were captured mainly through the relative price of tradable goods. The "classic" supply shock proxy used in the literature – the one that captures the effects of changes in the relative price of food and energy – was found to be significant for both Chile and Colombia. However, it was not relevant in the Brazilian case.

As to methodological issues, all countries used Phillips Curve based methodologies to estimate the natural rate of unemployment. Moreover, three of them (Brazil, Colombia and Venezuela) used only PC-based methodologies, attesting the

popularity of such a framework. In the case of Chile besides the PC framework two other methods were used: the unobserved components approach and the SVAR. See the Appendix for details.

The difficulties involved in the NAIRU estimation could be seen in the large degree of uncertainty surrounding point estimates. Although it is a well known fact in the literature that the NAIRU is estimated with great imprecision, the case of Venezuela stands out. Bujanda (2008) finds that the 90% confidence interval for the Venezuelan NAIRU goes from 8.4% to 20.1%, which is an incredible wide interval. Not surprisingly, except for the last two months of the sample, unemployment rates in Venezuela fluctuated inside the above range. Restrepo estimated a 95% confidence interval for the Chilean NAIRU going from 6.3% to 9.7%, a range within which the Chilean unemployment rate fluctuated during most of the sample. Given the above stylised fact da Silva Filho (2008) decided not to calculate parameter uncertainty, but rather to focus on model uncertainty – which according to him would provide a useful operational range – and provided NAIRU point estimates from five different models and two different approaches. Indeed, the range of the estimates proved to be much smaller than those above: around one percentage point (7.4%–8.5%). Nonetheless, he called to attention that NAIRU estimates are very sensitive to the choice and inclusion of supply shocks in the Phillips Curve.

Regarding the behaviour of the NAIRU the papers from Brazil and Colombia found evidence of a constant NAIRU. Note that in Brazil's case the evidence remained unaltered when the TV-NAIRU framework was used. In the case of Colombia, although the estimate is not rigorously constant, it fluctuates within such a narrow range that from a statistical viewpoint it can easily be accepted as being constant. Indeed, during the 22-year sample, different NAIRU estimates varied only from 0.4p.p. to 0.6p.p. For both Chile and Venezuela results were dependent on the method used. For Chile, besides the constant NAIRU estimate that comes out of the constant PC specification, the unobserved components framework also produced a fairly constant NAIRU (apart from the very beginning of the sample). On the other extreme the SVAR estimate was extremely volatile. Cyclicality is also a trademark of the Ball & Mankiw approach, which have been used by both Chile and Venezuela.

A common evidence among BCCV – regardless of which method is used – concerns the pattern of unemployment gaps, which were decreasing, and even becoming negative, towards the end of the samples. In the case of Venezuela, the unemployment

gap became increasingly negative since around 2005, and by the end of the sample unemployment was well below the NAIRU, as one could have guessed by looking at recent inflation rates (see Figure 2). In the case of Chile, the unemployment gap became negative – in all methodologies – at the end of the sample, while in Colombia it reached the NAIRU level at the very end of the sample. In its turn, the unemployment rate in Brazil began to decrease at the end of the sample, towards the highest NAIRU estimate.

5 – A Brief Assessment

This section carries out a brief assessment on the approaches used and results obtained by the four countries that joined the research project on the natural rate of unemployment. General comments will be given emphasis; however, some specific issues in the papers will be pinpointed as well. A good place to start is by assessing some features of the methods that have been used.

It was pointed out in the introduction that one likely explanation behind the small number of participants in the natural rate of unemployment group is the widespread use of the HP filter by economists in order to estimate a variable's potential level. I will not discuss the shortcomings and drawbacks of the HP filter – which are widely known – but it is worth mentioning the evidence found for Brazil on the relative *qualitative* forecasting performance of the PC. Da Silva Filho (2008) compared the qualitative forecasting accuracy of the PC framework under HP-based unemployment gaps and gaps derived from assuming different constant NAIRU hypotheses. The evidence showed not only that the HP-based forecasts had the second worst qualitative forecasting accuracy, but also that the implied forecasting errors did not reveal one crucial element in recent inflation dynamics in Brazil: the importance and pervasiveness of supply shocks. On the contrary, those errors were the only ones suggesting that excess demand was the main cause of inflation in Brazil during the period analysed, a result that is sharply at odds with the evidence.

This lead us to the Ball & Mankiw approach, since one key step in their method involves the use of the HP filter. NAIRU estimates from that approach showed a clear cyclical pattern (see Chile's paper in particular), which not only poses challenges for understanding why it is so volatile, but hardly makes it a viable benchmark. More importantly, since supply shocks – which are expected to be correlated with unemployment – are ignored in that approach, NAIRU estimates are likely to be biased.

Cyclicality was also a major issue in Chile´s SVAR NAIRU estimate, which showed amazing variability, almost overlapping with the unemployment series itself. Even though it is not clear to what extent this feature was the outcome of the particular VAR specification used, the above evidence call for caution about using such methods.

On the other extreme lay estimates from Phillips Curves that assume that the NAIRU is constant [equation (2)]. Obviously, what comes out from those models is a constant NAIRU estimate, by construction. Hence one could argue that the outcome is not reliable, since it is imposed rather than tested. That argument is not necessarily true and, therefore, does not invalidate the method. What it does imply is that it is crucial to assess if the model is congruent with the data. Hence one needs to check whether the model is well specified and, mainly, whether there is any evidence of structural breaks. Parameter stability is a key evidence for the latter issue.

Note, however, that a similar type of argument applies equally to the opposite case: one could claim that a TV-NAIRU estimate could actually be the result of mis-specification, instead of reflecting a truly time-varying process. This point is extremely important but has been largely ignored in the empirical literature, which has been "eager for variability". It fits perfectly to the increasingly use of the PC-UC framework [equations (4) and (5)] in the NAIRU literature. Indeed, note that one key issue in this approach is precisely the so-called "smoothness problem", which is the "tendency" of the non-observable variable estimate to show excess volatility. As puts Gordon (1997) "If no limit were placed on the ability of the NAIRU to vary each time period, then the time-varying NAIRU could jump up and down and soak up all the residual variation in the inflation equation." The literature has dealt with this problem by restricting the extent by which the TV-NAIRU can vary [e.g. King *et al*. (1995) and Gordon (1997)]. However, as mentioned above, excess volatility could actually stem from mis-specification, so when restricting variances one risks of not dealing with the true problem. Therefore, even though smoother estimates make more sense, inference could remain unreliable. Moreover, the issue of how volatile one should allow the NAIRU to be remains open, since this decision bears a large degree of arbitrariness.

The next important issue – which reflects clearly how challenging the NAIRU estimation is – refers to the uncertainty behind NAIRU estimates. Since Staiger *et al's*. (1996) remark that "...measures of the precision of these [NAIRU] estimates are strikingly absent from this literature." they have become more common, and today we know that uncertainty about the NAIRU is much larger than one would like, to the point

that it is reasonable to question the usefulness of those estimates for policy. Nonetheless, it is interesting to note that confidence intervals are often calculated just for the constant NAIRU case.[22] Indeed, both Chile and Venezuela calculated confidence intervals for the constant NAIRU case only. To make things worse, note that so far we have been talking about parameter uncertainty only, but not about model uncertainty, which is an issue that remains largely overlooked in the literature. This is particularly relevant given Stock and Watson's (1996) finding that NAIRU estimates "... can be sensitive to seemingly modest changes in specification of the estimating equation ..." Indeed, da Silva Filho (2008) found for Brazil that NAIRU estimates are very sensitive to the presence and choice of supply shocks. Hence, if model uncertainty is taken into consideration the degree of uncertainty about the NAIRU will be even larger.

This is particularly relevant given the evidence presented by da Silva Filho (2008) that NAIRU estimates for Brazil are very sensitive to the presence and choice of supply shocks. Similarly, Stock and Watson (1996) mention evidence for Canada that NAIRU estimates "... can be sensitive to seemingly modest changes in specification of the estimating equation ..." Hence, if model uncertainty is taken into consideration the degree of uncertainty about the NAIRU will be even larger.

Note that the lack of precision not only produces wide confidence intervals but also makes structural break testing more difficult. For example, there is a clear break in Chilean unemployment around 1999. Hence Restrepo (2008) estimated two PC: one up to 1998 and another one using the whole sample. However, even though NAIRU estimates seemed sufficiently different between them (7.4% and 8.3%) he was not able to formally reject the hypothesis that the NAIRU before and after 1998 was the same. Bujanda (2008) also found the same difficulty for Venezuela, even though NAIRU estimates for the periods before and after the supposed break were almost three percentage points apart (12.5% and 15.1%).

Another evidence that unveils the difficulties faced by BCCV to estimate the NAIRU refers to the size of the unemployment coefficient in the Phillips Curve. The sum of the coefficients on lagged unemployment [i.e. $\beta(L)$] amounted to just -0,001 in the case of Chile, which implies an extremely large sacrifice ratio. Although that sum is much higher for Venezuela (-0.05), it still implies very large sacrifice ratios. For Brazil,

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[22] One could raise the hypothesis that part of that wide uncertainty could stem from estimating a constant NAIRU when it actually is time-varying. However, Stock and Watson (1996) show evidence that uncertainty about the NAIRU remains large across methodologies.

estimates varied from -0.05 to -0.19. This timid role played by unemployment on inflation dynamics suggests the existence of room for improvements in the specification of the PC. More specifically, it could be that supply shocks were not properly accounted for, leading to a bias in the unemployment coefficient.

With the exception of Brazil's paper – where several supply shocks proxies were built – the number of proxies used were very small, being usually restricted to the two most used in the U.S. NAIRU literature (see the Appendix). Given the potential large gains involved in properly capturing supply shocks effects, it is certainly worthwhile to spend more time on this issue. Note that in Colombia's paper supply shocks effects were not controlled for, while in Venezuela's shocks were apparently not demeaned. In both cases this implies bias in the NAIRU estimates.

Perhaps the tiny unemployment coefficient in the Chilean case is related to the choice of the dependent variable in the PC. Instead of using the first difference of inflation Restrepo (2008) used the deviation of inflation from its HP trend. This poses some problems. For example, how to interpret the implied "NAIRU", since what comes out of the model is not the unemployment rate consistent with stable inflation, but rather that rate consistent with inflation being on its trend. Estimates could be very different in both cases, especially if inflation is not stable along the sample.

The pattern of each country's unemployment gap also deserves some comments. For example, da Silva Filho (2008) found a positive unemployment gap throughout the eleven-year sample for Brazil. This is an unusual result, especially when compared to the results from those methods that read a variable's potential level as some form of averaging (i.e. do not allow persistent deviations from trend), such as the HP filter. Note, however, that the unemployment gap was negative for around eleven years (1987–1997) in Colombia as well, and positive in the following eight years (1988–2005), according to Arango (2008). In Chile, the gap remained negative for around ten years (1989–1998), and positive in the following six years – for both the constant NAIRU and UC cases – according to Restrepo (2008). Hence, from that perspective, Brazil's results are not unusual. However, more important than the actual duration of periods with one-sided unemployment gaps is to understand the results. In this regard most of the papers could have gone deeper in confronting NAIRU estimates with the country's economic history, in order to provide some intuition and assess the plausibility of the results. This is even more important in those cases where NAIRU estimates are very volatile.

6 – Final Remarks

Blanchard and Katz (1997) said ten years ago that "Economists are a long way from having a good quantitative understanding of the determinants of the natural rate, either across time or across countries". Their remark remains incredibly valid today. The well-known difficulties behind the NAIRU estimation persist to challenge those who join the quest. For example, it continues to be estimated with great imprecision, which not only is a reflection of such difficulties but also raises questions about its usefulness for monetary policy. Also, recent evidence has shown a widespread flattening of the Phillips Curve across countries, perhaps revealing structural changes in the economic environment. However, better policymaking – with the increasing emphasis on controlling inflation – could also be behind that phenomenon.

As a matter of fact I think their remark was – and continues to be – a little bit optimistic, since despite the important advances in the area a better understanding on the *qualitative* determinants of the natural rate is still needed. An example that I found particularly useful in this regard are Weiner's (1993) predictions of the U.S. natural rate, made just before the appearance of the "new economy" in the 1990s. After a careful analysis of some structural determinants of the natural rate in the U.S. he predicted that it was likely to rise in the following years and, therefore, that the inflation risk was rising. However, what followed was just the opposite: both unemployment and inflation fell sharply during the 1990s in the U.S.[23]

Hence, the numerous difficulties faced by Brazil, Chile, Colombia and Venezuela when estimating the NAIRU were not a surprise. For example, the estimated confidence intervals are very wide, especially in the Venezuelan case, where it reaches almost twelve percentage points. Moreover, in most papers results proved to be highly dependent on the particular method used, which adds to the parameter uncertainty. Also, the unemployment coefficient in the Phillips Curve seems too low, implying incredible large sacrifice ratios in some cases (e.g. Chile).

Another interesting finding is the importance of supply shocks for inflation dynamics, especially in the case of Brazil. Indeed, Brazilian data showed an unexpected positive relation between changes in inflation and unemployment, suggesting both the

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[23] Note that some of the factors claimed to explain the fall in the NAIRU during the 1990s not only are not present anymore, but have become playing in the opposite direction (e.g. the deflationary effects of globalisation). Even so the current rate of unemployment in the U.S. – which has recently increased due to the sharp economic slowdown – lies well below the mid-1990s' natural rate estimates.

relevance of supply shocks and the difficulties in uncovering the NAIRU. Among the supply shocks used, exchange rate shocks seem to play a central role for most countries. Moreover, besides the dependency on the particular methodology used, found in most papers, the evidence for Brazil shows that NAIRU estimates are very sensitive to the inclusion and choice of supply shocks.

Among the many methods available in the literature – and used in the papers – the Phillips Curve framework proved to be the most popular, being adopted by all countries. Some reasons behind such popularity are the appeal of modelling the link between inflation and unemployment explicitly and its flexibility. For example, the PC can be used together with the unobserved components technology in order to allow for a time-varying NAIRU (TV-NAIRU).

Nonetheless, a frequent uncomfortable feature of those methods that allow the NAIRU to vary is either a too volatile NAIRU or an estimate with marked cyclical pattern. Those features pose great challenges for both explaining the rationale behind such changes and using the NAIRU as a benchmark for policy. Moreover, it was called to attention that a TV-NAIRU could mainly reflect mis-specification, and not a genuine time-varying process. Hence, it is essential to check model's adequacy in every way possible in order to make reliable inferences. I would say that in more flexible frameworks the care should be even greater. Worrisome evidence regards the widely use by economists of the HP filter to estimate the NAIRU. The evidence from Brazil shows that HP-based unemployment gaps provide very poor qualitative inflation forecasts and completely miss the importance of supply shocks in recent Brazilian inflation dynamics.

The main practical advice that comes out from this joint research project is that, despite all the difficulties in estimating the NAIRU, there seems to be much room available for improvement, especially those stemming from better modelling and better care with the data. For example, many specifications retained insignificant variables and showed signs of mis-specification. Also, given the importance of supply shocks in inflation dynamics it will certainly pay off to spend some time trying to come up with proxies that better capture those shocks. Such improvements are very likely to narrow down the uncertainty about the NAIRU, as well as to reveal a greater role for unemployment in inflation dynamics, among other benefits.

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Appendix[24]

	BRAZIL	CHILE	COLÔMBIA	VENEZUELA
Inflation	Headline	Core Inflation, SA	ex-Food & Elect., SA	Headline
Unemployment	Difference Stationary / SA	Trend Stationary / SA	Difference Stationary / SA	Difference Stationary / SA
Supply Shocks	Several Supply and Relative Price Shocks Proxies (see paper for more details). Obs: Food & Energy shock not relevant. / Demeaned	$\pi_t^{ex-food\&fuel} - \pi_t^{core}$ $\pi_t = \Delta\ln CPI_t$ / $\Delta\ln RER_t$ / Demeaned	No supply shocks / – / –	$\Delta\ln\left(\dfrac{CPI^{food\&bev.}}{CPI}\right)$ / $\Delta\ln RER_t$ / Not Demeaned
Methodologies	PC (cte NAIRU) NAIRU point estimates vary from 7.4% to 8.5%.	PC (cte NAIRU) NAIRU = 8.2% 95% interv. = 6.3%-9.7% Obs: struc. break in 1998. (7.4% until 1998.6) UC Model (PIB + Unemp.) PIB: RW + Stochastic Drift + AR2 Cicle. UN: RW + AR2 Cicle. Obs: Cycles are correlated. (NAIRU is very stable, around 8%; 8.2% at the end).	TV-NAIRU Demographic adjusted It varies due to changes in the relative size of demographic groups in the labour force over time (Weiner, 1993). But within each group the NAIRU is assumed to be constant. Basic group: (men, aged 31-40) head of household	PC (cte NAIRU) NAIRU ≈ 14% 90% interval (8.4%-20.1%)

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[24] PC, RW and UC stand for Phillips Curve, random walk and unobservable components, respectively. TV-NAIRU means time-varying NAIRU. For more details on each country's procedure see the respective country papers.

	BRAZIL	CHILE	COLÔMBIA	VENEZUELA
Methodologies	PC (TV-NAIRU) PC + UC (NAIRU modelled as a RW) NAIRU is found to be constant at 8.5%.	PC (TV-NAIRU) 1) Ball & Mankiw (varies a lot; cyclical; 7.4% at end) 2) Recursive estimates (stable; similar to UC; 8.3% end) 3) Structural VAR ($\Delta y^r; \Delta u; \pi^I$) - 3 Shocks: supply: labour and productivity shocks; and demand shocks (varies a lot, almost overlaps with unemp. 8.0% at end)		PC (TV-NAIRU) 1) Ball & Mankiw (but including shocks) (falls since 2002: max. 17% (02), min 9% (07) 2) PC + Spline (2, 3 knots) $\beta(1)$ not significant Looks like HP (2 knots) **Obs:** NAIRU's dynamics have important differences. 3) Discret Break Model Break not statistically significant. NAIRU: 15.1% (2000.1-04.3) and 12.5 (04.4-06.6)
Unemp. Coeff.	0.12 (average) (significant at 1%)	0.001 (cte NAIRU) (significant at 1%)	Not available	-0.05 (significant at 10%)
Unemp. Lags (U)	t-2 and t-3 (Q)	t-1 to t-4 (M)/t-1 to t-4 (Q)	–	t-1, t-2 and t-3 (M)
NAIRU Estimates	7.4% – 8.5% (point estimates)	7.4% – 8.3% (point estimates, end of period)	NAIRU = 11.9%, very stable (0.5 p.p.)	10% – 14% (point estimates, end of period)
Confidence Interval	7.4% – 8.5% (range of point estimates)	6.3% – 9.7% (based on the constant NAIRU model)	Not calculated	8.4% – 20.1% (based on the constant NAIRU model)
	Obs: positive gap during the sample.	**Obs:** negative gap since 2006.	**Obs:** positive gap in 1998-2005.	**Obs:** negative gap since 2004.

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