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A Tale of Three Gaps: Unemployment, Capacity Utilization and Output*

Sergio Afonso Lago Alves† Arnildo da Silva Correa‡

Abstract

The Working Papers should not be reported as representing the views of the Banco Central do Brasil. The views expressed in the papers are those of the author(s) and do not necessarily reflect those of the Banco Central do Brasil.

We assess the relationship between unemployment, capacity utilization for the industrial sector and inflation in Brazil using disaggregated Phillips curves for the tradable and nontradable sectors. Using quarterly Brazilian data for 1999Q2-2012Q4, we estimate the NAIRU, NAICU and output gap with Kalman filter. The results suggest that the unemployment gap is the relevant demand variable to explain inflation of nontradable goods, while the capacity utilization gap is important for inflation of tradable goods. There is evidence of substantial reduction in the NAIRU in recent years, and it has been above the unemployment rate since mid-2010. The results suggest a dichotomy in the Brazilian economy: while the manufacturing sector shows poor performance and difficulties to react, the labor market is heated, generating pressures on the output gap. Our study also emphasizes possible biases produced both by aggregate estimations in a dichotomous environment, and by considering simple HP-filtering methods.

Keywords: NAIRU, NAICU, Industrial Capacity Utilization, Unemployment, Output Gap, Monetary Policy.

JEL Classification: E3, E32, E52, J01, J64

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"It was the best of times, it was the worst of times, it was the age of wisdom, it was the age of foolishness, it was the epoch of belief, it was the epoch of incredulity, it was the season of Light, it was the season of Darkness, it was the spring of hope, it was the winter of dispair, we had everything before us, we had nothing before us, we were all going direct to Heaven, we were all going direct the other way."

Charles Dickens, A Tale of Two Cities

1 Introduction

Brazil has been experiencing an odd economic instance since 2005. Employment seems to be sky-rocketing and almost immune to many shocks that hit the Brazilian economy during the period, including the second great recession of 2007-2009. Over the sample, employment seems not to be correlated at all with production or capacity utilization. Since 2010, in particular, the correlation between employment and production seems to be negative. Indeed, capacity utilization and GDP growth have been decreasing, whereas employment has remained in its steadily increasing path. Stylized facts are shown in Section 2. On top of that, economists have been facing a hard time to find a positive correlation between employment and inflation, which should be a trivial task in most countries. Indeed, some economists have reported difficulties in estimating significant coefficients for the employment gap (or unemployment) in empirical aggregate Phillips curves (e.g. Delfim Netto (2013), Mendonca et al. (2012) and Minella et al. (2003)).

Hence, a puzzle arises in reconciling this dichotomous behavior between employment, capacity utilization and production, and explaining the lack of correlations between employment/production and employment/inflation.

In order to put some light into solving this puzzle, we look into disaggregate measures to find that strong idiosyncrasies in two important production sectors, with opposite directions, are at play. In particular, we explore the relation between employment, capacity utilization, output, and inflation in the sector of non-traded goods, whose production is intensive in labor, and the (manufacturing) sector of traded goods, whose production is intensive in capital.

We do not seek to explain the mechanisms behind this dichotomy. We take for granted the interpretation called "two blades of a scissor", coined by Pastore et al. (2012) and Pastore (2012). Their analysis is based on a model with two sectors for the Brazilian economy. The explanation for the slowdown in the manufacturing sector is that labor market pressures on wages caused by the dynamism of the service sector, coupled with the drop in productivity, increases the unit cost of labor. The manufacturing sector, assumed to be nearly price taker, is unable to pass on increased costs to prices and have reduced profit margins.

We rather explore its consequences. We use an empirical semi-structural approach to model Phillips curves[1] in both sectors, and infer the non-accelerating inflation rate of unemployment (NAIRU) and non-accelerating inflation rate of capacity utilization (NAICU) by means of Kalman filtering. In this dichotomous context, it is difficult to define what are the relevant demand variables to be used in empirical aggregate Phillips curves. Current consensus is that Phillips curves should be total (theoretical) or partially (semi-structural) funded in micro-economic theory. One of the strong assumptions behind most theoretical models is that all sectors are homogeneous in the use of production factors. Under weaker assumptions, however, one cannot theoretically justify functional forms in which only the aggregate output gap or unemployment gap affects aggregate inflation.[2]

Nevertheless, the popularity of theoretical models with homogeneous firms contributed to the use of only the output gap in most empirical exercises[3], even in Brazil (e.g. Bogdanski et al. (2000), Alves and Muinhos (2003), Tombini and Alves (2006) and Correa and Minella (2010)).[4] In Brazil, the use of employment in empirical Phillips curves is still uncommon.[5] However, considering separately how labor and capital affect inflation seems crucial to understand the transmission mechanisms of monetary policy and responses to shocks, in a context characterized by a weak performance in the manufacturing sector

[1]Phillips curves are refinements of contemporary empirical relationship shown in Phillips (1958), where the change rate of nominal wages has a negative correlation with the unemployment rate.

[2]For the derivation of the simplified functional form, in which the aggregate inflation rate is affected by a single gap measure, it is necessary to take several strong assumptions, e.g. inflation rates of all sectors have the same inertial behavior, productivity shocks are the same in all sectors, there is no wage rigidity, and there are no frictions in the labor market. For example, by assuming specific capital, Woodford (2005) shows that the Phillips curve should have both the output gap and the investiment gap. In order to include a more realistic labor market, by embedding search frictions, the Phillips curve includes the unemployment gap in addition to the aggregate output gap (e.g. Alves (2012), Blanchard and Gali (2010), Christiano et al. (2011), Gali (2010), Gertler et al. (2008), Gertler and Trigari (2009), Ravenna and Walsh (2008, 2012), Thomas (2008, 2011) and Walsh (2005)).

[3]Important references are found in Cogley and Sbordone (2008), Coibion et al. (2012), Coibion and Gorodnichenko (2011), Linde (2005), Rabanal and Rubio-Ramirez (2005), Rudd and Whelan (2005) and Smets and Wouters (2003, 2005, 2007), among others.

[4]In Brazil, estimates of Phillips curves with measures of marginal cost are rare (e.g. Alves and Areosa (2005), and Areosa and Medeiros (2007)).

[5]Good references are found in Mendonca et al. (2012) and Minella et al. (2003).

coupled with large employment rates.

We find that the correlation puzzle only arises on aggregate measures. Indeed, in Section 4 we run an aggregate Phillips curve, using the unemployment gap obtained by ordinary HP-filtering, and our results support the findings in the Brazilian literature, i.e. the coefficient on the unemployment gap is not significant, even in the best specification. We also replicate this exercise using instead the capacity utilization gap and GDP gap, all of them obtained by ordinary HP-filtering. The basic results remain.

Yet individually looking at both sectors, we find that employment is an important variable to explain inflation in the sector of non-traded goods, while it is the inflation rate of traded goods that is highly correlated with output and capacity utilization.

We also find that the NAIRU has systematically decreased in Brazil, but not as much as the actual unemployment rate. While the its central path was close to 11-12% by 2002, it has decreased to around 6.3% in late 2012. Additionally, our results suggest that the unemployment rate has been below the NAIRU since mid-2010. Our method does not allow us to seek for the reasons why NAIRU has fallen. However, the indirect evidence suggests that it has indeed decreased, otherwise the inflation rate would have strongly reduced in sectors intensive in labor. Other than that, Brazilian government has implemented some reforms intended to improve the labor market since the early 2000's. Even though our results are not meant to explore the consequence of such structural changes, we believe that they may have affected the NAIRU level.

In the manufacturing sector, our results suggest an increase in NAICU over the sample. By the end of 2012, it has been above the actual capacity utilization for the industrial sector. We highlight, however, that our central estimates of NAIRU and NAICU carry a high level of uncertainty, as in any empirical exercise of this nature.

Finally, the estimated three gaps (unemployment gap, capacity utilization gap and the output gap) highlight the role of the labor market as a source of pressure on economic activity and inflation, and emphasize the dichotomy experienced by the Brazilian economy. We infer two sources of pressure acting in opposite directions on the output gap in the last two years. On the one hand, our results suggest that the manufacturing sector has been more sluggish (negative capacity utilization gap) in recent years than what a simple HP filtering suggests, pressing the economic activity down. On the other hand, the labor market has been stronger (negative unemployment gap) than what a simple

HP filtering suggests, pressing the economic activity up.

In this paper, we find evidence that the use of HP filtered gaps might have contributed to the correlation puzzle. Indeed, as different productive sectors use factors in different intensities, the dynamics of sectorial inflation rates might behave very differently in response to shocks. Therefore, using a single Phillips curve to explain the aggregate inflation rate as a function of the aggregate output gap, or the unemployment gap, generates specification and/or omitted variable bias. Moreover, gap variables obtained by HP filtering (Hodrick and Prescott (1997)), or other filtering method that does not embed economic structure, might have serious measurement error problems. And it is a well known result in the econometric literature that the use of covariates with measurement error causes attenuation bias toward zero.

The rest of the paper is organized as follows. Section 2 presents stylized facts. Section 3 presents the empirical semi-structural model. Section 4 presents the estimation results, the estimated NAIRU and NAICU paths, and the three estimated gaps. Section 5 concludes.

2 Stylized facts

The unemployment rate, U_t, as measured by the Brazilian Institute of Geography and Statistics (IBGE), has been decreasing since mid-2003, as shown in panel (A) of Figure 1. The reduction in unemployment also seems to have been almost acyclical and immune to many shocks that hit the Brazilian economy in the period. On the other hand, the capacity utilization for the industrial sector rate, CU_t, as measured by the National Confederation of Industry (CNI), has been quite volatile around an almost constant average.

Panel (B) shows that year-over-year changes in the unemployment rate remain negative in most part of the period and almost acyclical, while GDP[6] and industrial production (general index)[7] growth rates vary widely. In particular, the large decline in the Brazilian economic growth during the 2007-2009 financial crisis was accompanied only by a slight increase in unemployment. There was also no increase in unemployment in 2011-2012, when GDP and industrial production growth have slowed down. The capacity utilization

[6] Measured and released by IBGE.
[7] Measured and released by IBGE.

for the industrial sector, on the other hand, has strongly decreased during the period.

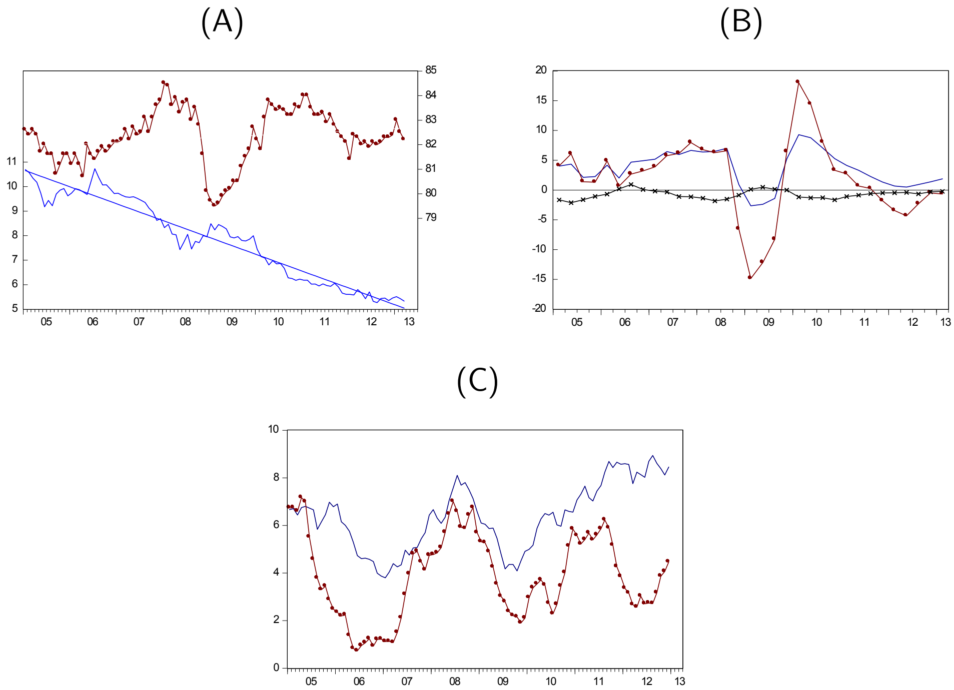

Figure 1: Unemployment, capacity utilization, GDP, industrial production and inflation rates

Note: Panel (A): capacity utilization for the industrial sector (red circles), Unemployment rate and its linear trend (blue).
Panel (B): Industrial production growth rate (YoY) (red circles), GDP growth rate (YoY) (blue), first difference of unemployment rate (black stars).
Panel (C): Traded goods 12-month inflation rate (red circles), Non-traded goods 12-month inflation rate (blue).

This evidence suggests a dichotomy in the Brazilian economy in recent years: low and declining unemployment rates coexist with low GDP and industrial production growth rates. In fact, after growing 7.5% in 2010, Brazil's GDP slowed to 2.7% in 2011 and 0.9% in 2012, while industrial production grew only 0.3% in 2011 and decreased 2.7% in 2012. On the other hand, the unemployment rate, which was around 6.7% in the 2010 average, declined to 6.0% and 5.5% in 2011 and 2012, respectively, and reached 4.6% in December 2012, the lowest level of the series so far.

Panel (C) shows the different paths of traded and non-traded goods 12-month inflation rates. While prices of traded goods increased 4.4% in 2011 and 4.5% in 2012, prices of non-tradables rose 8.6% and 8.5%. The production of the first class of goods is associated with the manufacturing sector, which is intensive in capital, while the latter is associated with the non-manufacturing sector, which is intensive in labor. Therefore, pressures coming from the labor market are particularly important for the nontraded goods sector, especially the service sector, where payroll represents a significant portion of total production costs.[8] The sector of traded goods is more exposed to competition from imported products, which limits their ability to adjust prices. The distinct inflation dynamics of both sectors are a direct consequence of the sectoral dichotomy and suggests that it is not possible to characterize the economy as a whole using a model with a single aggregate Phillips curve.

3 The model[9]

For simplicity, we assume that the inflation rates for traded and non-traded goods are good proxies for the inflation rates of the manufacturing and non-manufacturing sectors. To avoid collinearity problems between covariates, we only consider the most intensive production factor in each sector. Thus, the relevant demand variable for the Phillips curve of non-traded goods is the unemployment gap with respect to NAIRU, while the relevant demand variable for the Phillps curve of traded goods is the capacity utilization gap with respect to NAICU.[10]

Both Phillips curves are jointly estimated by full-information maximum likelihood (FIML), while the estimates of NAIRU and NAICU are obtained by Kalman filtering. We acknowledge the fact that no filtering method is free of problems (Canova (1998) and Canova and Ferroni (2011)). However, we assume that filters containing greater economic structure have more chances to extract the correct information.

In one approach, we use auxiliary measures obtained by the HP filter as initial paths for the estimation of NAIRU and NAICU. The Kalman filter is used to fine-tune those initial paths. This strategy helps the convergence of the Kalman filter.

We also consider a dynamic linear model (DLM), in which the trajectories of the latent variables, NAIRU and NAICU, are described as random walks with stochastic drifts.[11]

[8] Of course, wage pressures generated by a booming labor market end up affecting the costs in the tradable sector as well.

[9] The model we present and estimate in this paper is meant for academic purposes only. It is not meant for forecasting and monetary policy implementation by the Banco Central do Brasil.

[10] Indeed, we find that considering both the unemployment and capacity utilization gaps in each Phillips curve leads to identification issues, characterized by numerical instability, coefficients undeterminacy, and economic meaningless paths (with negative regions) for NAIRU and NAICU.

[11] Great references on dynamic linear models (DLM) and inference using the Kalman filter are Hamilton

In the best specification, the model has the following form:

$$\begin{aligned}&\pi_t^{nt} = \lambda_1 \pi_{t-1}^{fr} + \lambda_2 E_t \pi_{t+1}^{nt} + \lambda_3 \pi_{t-1}^{*} + \lambda_4 \hat{u}_t + \boldsymbol{\beta}' \mathbf{X}_{t-j} + \xi_t^{nt} \\ &\lambda_1 + \lambda_2 + \lambda_3 = 1 \quad ; \ \xi_t^{nt} \sim N\left(0, \sigma_{nt}^2\right)\end{aligned} \tag{1}$$

$$\begin{aligned}&\pi_t^{tr} = \gamma_1 \pi_{t-1}^{fr} + \gamma_2 E_t \pi_{t+1}^{tr} + \gamma_3 \pi_{t-1}^{*} + \gamma_4 \hat{c}_{t-2} + \boldsymbol{\theta}' \mathbf{Z}_{t-l} + \xi_t^{tr} \\ &\gamma_1 + \gamma_2 + \gamma_3 = 1 \quad ; \ \xi_t^{tr} \sim N\left(0, \sigma_{tr}^2\right)\end{aligned} \tag{2}$$

$$\begin{aligned}&\pi_t^{fr} = \omega_t^{tr}\left(\pi_t^{tr} - \xi_t^{tr}\right) + \left(1 - \omega_t^{tr}\right)\left(\pi_t^{nt} - \xi_t^{nt}\right) + \xi_t^{fr} \\ &\xi_t^{fr} \sim N\left(0, \sigma_{fr}^2\right)\end{aligned} \tag{3}$$

The Phillips curve for the inflation rate of non-traded goods, π_t^{nt}, is described in equation (1), where $E_t(\cdot)$ is the expectation operator conditional on the information set available at period t, $\hat{u}_t$ is the unemployment gap (defined below) and $\mathbf{X}_t$ collects zero-meaned proxies for supply shocks. Equation (2) is a Phillips curve for the inflation rate of traded goods, π_t^{tr}; $\hat{c}_t$ is the capacity utilization gap (defined below) and $\mathbf{Z}_t$ collects zero-meaned proxies for supply shocks ($\mathbf{X}_t$ and $\mathbf{Z}_t$ may have non-empty intersection). Equation (3) imposes consistency of sectorial inflation rates with the aggregate free-market inflation rate, π_t^{fr}, where ω_t^{tr} is the time-varying weight of the inflation rate of traded goods and ξ_t^{fr} is a modelling error term. Moreover, $\pi_t^{*} = \left(\Delta e_t + \pi_t^{f}\right)$ is the inflation rate of imported goods, in domestic currency prices, measured by the (log) variation of the nominal exchange rate, Δe_t, added to the external inflation rate, π_t^{f}; ξ_t^{nt} and ξ_t^{tr} are error terms, and $[\lambda_1, \lambda_2, \lambda_3, \lambda_4, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \boldsymbol{\beta}, \boldsymbol{\theta}, \sigma_{nco}^2, \sigma_{com}^2, \sigma_{liv}^2, \sigma_d^2]$ is the parameter vector to be estimated. We impose verticality restrictions on the coefficients of the Phillips curves. Finally, $u_t \equiv -\log\left(1 - U_t\right)$ and $c_t \equiv \log\left(UCI_t\right)$ are logarithmic transformations of the unemployment rate, U_t, and the capacity utilization rate, UCI_t.

Equation (3) deserves some comments. Note that the terms in parentheses are the fitted components of the other two equations. The sum of those values, weighted by their respective time-varying weights, equates the fitted component of the aggregate free-market inflation rate. If the weights ω_t^{com} were constant over time, this equation would not add any information to the system. Moreover, the variance-covariance matrix of the error terms would be singular and the joint estimation of the three equations would

(1994), Prado and West (2010) and West and Harrison (1997). For DLMs applications in macroeconomic models, see Basdevant (2003).

be impossible. It is the fact that the weights are time-varying that allows us to jointly estimate the system.

Now we describe the way we compute the unemployment gap, $\hat{u}_t$, and the capacity utilization gap, $\hat{c}_t$. In this work we use two different strategies and compare their results. The first is to adopt the standard approach for estimating latent variables. We will call this strategy as model M_S (standard approach). In this approach, we define the unemployment gap as the difference between the unemployment rate and the NAIRU, and directly model the NAIRU as a state variable. The same procedure is used for the capacity utilization gap and the NAICU. Thus, in model M_S we jointly estimate the system (1)-(3), with the following state variables:

$$(M_S) \qquad \begin{array}{ll} u_t^n = u_{t-1}^n + u_{t-1}^{dr} & ;\ c_t^n = c_{t-1}^n + c_{t-1}^{dr} \\ u_t^{dr} = u_{t-1}^{dr} + \zeta_t^{ud} & ;\ c_t^{dr} = c_{t-1}^{dr} + \zeta_t^{cd} \\ \zeta_t^{ud} \sim N\left(0, \sigma_d^2\right) & ;\ \zeta_t^{cd} \sim N\left(0, \sigma_d^2\right) \end{array} \tag{4}$$

where $u_t^n \equiv -\log\left(1 - NAIRU_t\right)$ and $c_t^n \equiv \log\left(NAICU_t\right)$ are logarithmic transformations of NAIRU and NAICU, and the gap variables are defined as $\hat{u}_t \equiv u_t - u_t^n$ and $\hat{c}_t \equiv c_t - c_t^n$.

In the second approach, we use series obtained by purely statistical filters as initial paths for the NAIRU and NAICU. The Kalman filter fine tunes over those initial guesses. For simplicity, we chose the HP filter as the auxiliary filter. We will call this procedure as model M_A (auxiliary variables). To see how the procedure works, we write the NAIRU and NAICU as:

$$u_t^n = u_t^{hp} + cor_t^u \quad ;\ c_t^n = c_t^{hp} + cor_t^c \tag{5}$$

where $u_t^{hp} \equiv -\log\left(1 - NAIRU_t^{hp}\right)$ and $c_t^{hp} \equiv \log\left(NAICU_t^{hp}\right)$ are estimates obtained by HP filtering in a first step, and cor_t^u and cor_t^c represent corrections obtained by the Kalman filter. Thus, in model M_A, we jointly estimate the system (1)-(3) with the following state variables:

$$(M_A) \quad \begin{array}{ll} cor_t^u = cor_{t-1}^u + cor_{t-1}^{ud} & ;\ cor_t^c = cor_{t-1}^c + cor_{t-1}^{cd} \\ cor_t^{ud} = cor_{t-1}^{ud} + \eta_t^{ud} & ;\ cor_t^{cd} = cor_{t-1}^{cd} + \eta_t^{cd} \\ \eta_t^{ud} \sim N\left(0, \tilde{\sigma}_d^2\right) & ;\ \eta_t^{cd} \sim N\left(0, \tilde{\sigma}_d^2\right) \end{array} \tag{6}$$

where $cor_t^u = u_t^n - u_t^{hp}$ and $cor_t^c = c_t^n - c_t^{hp}$. In order to simplify the estimation process of model M_A, we impose $\tilde{\sigma}_d^2 = \sigma_d^2$, where the latter was estimated in model M_T.

There is at least one apparent advantage in using model M_A over M_S. The corrections are stationary. Thus, it will be easier for the Kalman filter to infer them and fine tune the auxiliary paths of NAIRU and NAICU.

Note that random walks with stochastic drift specifications are able to capture the vast majority of stationary and non-stationary processes in finite samples. Thus, the model allows the latent variables to have stationary patterns in some parts of the sample and non-stationary patterns in others.

Both methods use a recursive procedure, consisting of two steps, which can improve identification. As a variation of the Dempster et al. (1977) Expectation-Maximization (EM) method, in the first step, we use the central values of the smoothed NAIRU and NAICU latent variables, obtained in the previous step, to estimate the model parameters.[12] In the second step, we fix the parameters of the unemployment and capacity utilization gap obtained in the previous step, and infer the dynamic distributions of the NAIRU and NAICU. To start the recursive process, we use the auxiliary measurements obtained by the HP filter. The two steps are repeated until the system parameters satisfy a convergence criterion.

As a counterfactual exercise, we also estimate an aggregate model for the free-market inflation rate, π_t^{fr}, considering (in separate estimations) three measures of economic activity:

$$\begin{aligned} &\pi_t^{fr} = \varphi_1 \pi_{t-1}^{fr} + \varphi_2 E_t \pi_{t+1}^{fr} + \varphi_3 \pi_{t-1}^{*} + \varphi_4 \hat{\chi}_{t-j} + \boldsymbol{\phi}' \left(\mathbf{X}_{t-j}, \mathbf{Z}_{t-l} \right) + \xi_t^{fr} \\ &\varphi_1 + \varphi_2 + \varphi_3 = 1 \quad ; \ \xi_t^{fr} \sim N\left(0, \sigma_{fr}^2\right) \end{aligned} \tag{7}$$

where $\hat{\chi}_t$ represents one of the three gaps: unemployment gap, $\hat{u}_t$, capacity utilization gap, $\hat{c}_t$, or GDP gap, $\hat{y}_t$. The gaps are estimated using the standard HP filter or the methods just described, and the lag j is chosen to optimize usual information criteria.

[12] Smoothed values consider the whole information set, i.e., central values are obtained by $\bar{u}_t^n = E\left(u_t^n | \{Y_\tau\}_{\tau=1}^T\right)$ and $\bar{c}_t^n = E\left(c_t^n | \{Y_\tau\}_{\tau=1}^T\right)$, where Y_t is the vector of observable variables (endogenous and exogenous) in period $t \in \{1, T\}$.

4 Estimation

We estimate the system using FIML, while the estimates of NAIRU and NAICU are obtained by Kalman filtering. The estimation is carried outusing seasonally adjusted quarterly data in the period 1999Q2-2012Q4. The measures of inflation for free prices, traded and non-traded goods are from the Broad National Consumer Price Index (IPCA), released by IBGE. Time-varying weights come from the correspondents IPCA basket. We have used slightly different measures of inflation rates for traded and non-traded goods, as described in Banco Central do Brasil (2011). The method incorporates the new structure of consumption patterns, according to the IBGE's Household Budget Survey (POF) 2008-2009. The measure of foreign inflation is given by the variation of the Commodity Research Bureau (CRB) Index.

The capacity utilization variable is released by CNI.[13] The measure of unemployment adopted for most of the period is the rate of open unemployment, with a reference period of 30 days from the IBGE's Monthly Employment Survey (PME). IBGE conducted important methodological changes in the calculation of unemployment in 2002 to conform its measurement to international standards, which means that this information is available only for the period from March 2002 on. To obtain a longer data series, the unemployment data of IBGE were combined with the series of aggregate unemployment measured by the Survey of Employment and Unemployment (PED), released by DIEESE/Fundação SEADE-SP (from April 1999 to February 2002). This series measures the unemployment rates in the metropolitan regions of Belo Horizonte, Fortaleza, Porto Alegre, Recife, Salvador, São Paulo and Distrito Federal. Due to this change in the unemployment series, we also performed an estimation using data from IBGE only, i.e., constraining the sample to 2002Q2–2012Q4.

There are also additional variables proxying supply shocks in the Phillips curves, represented by the vectors $\mathbf{X}_t$ and $\mathbf{Z}_t$. Several variables were tried as controls for these shocks, such as changes in relative prices, in commodity prices, in oil prices, changes in the minimum wage etc. Of those variables, only two were significant in the equation for inflation of traded goods: the variable de_t, that captures the misalignment of prices at wholesale and retail (measured by the difference between the (log) Wholesale Price Index

[13] We also performed estimations using data from Fundação Getulio Vargas – FGV. The results did not change qualitatively.

– IPA-FGV and the (log) Consumer Price Index – CPI-FGV); and $shtr_t$, capturing shocks to commodity prices, as measured by the CRB index (measured in Brazilian currency) gap from its HP trend.

The presence of inflation expectations terms, $E_t\pi_{t+1}^{nr}$, $E_t\pi_{t+1}^{tr}$ and $E_t\pi_{t+1}^{fr}$, in the Phillips curves cause an endogeneity problem that needs to be addressed. Thus, we use a two-stage procedure to estimate the model. The first stage involved regressing the actual values of inflation of tradable and non-tradable goods in the period $t+1$ on instrumental variables. Then, using the fitted components as the expectations variables in the second stage. In this second stage, all the equations of the model are jointly estimated. The instruments used for $E_t\pi_{t+1}^{nr}$ were $(1/2)\sum_{j=1}^{2}\pi_{t-j}^{nr}$, π_{t-1}^{tr} and de_{t-1}. The instruments for $E_t\pi_{t+1}^{tr}$ were π_{t-1}^{nr}, π_{t-1}^{tr}, π_{t-1}^{ipca} and de_{t-1}. In the case of the couterfactural model, the instruments for $E_t\pi_{t+1}^{fr}$ were π_{t-1}^{fr}, π_{t-1}^{ipca} and de_{t-1}.

We first estimate the counterfactual model (7) using only HP-filtered measures of activity gaps. Table 1 shows our results. The counterfactual results suggest that using HP-filtered gaps, i.e. not considering the economic structure, leads to bad estimates on the coefficient of the activity gaps, no matter which variable we use. In particular, the model with unemployment gap seems to outperform the others. However, the coefficient on $\hat{u}_t$ is significant only at 9.2%.

Table 1: Counterfactual Model – Results with HP-Filtered Gaps

	M_1 $(\hat{u}_t)$	M_2 $(\hat{c}_{t-2})$	M_3 $(\hat{y}_{t-3})$
Aggregate Phillips Curve			
π_{t-1}^{fr}	0.417^{***} (0.109)	0.424^{***} (0.119)	0.418^{***} (0.123)
$E_t\pi_{t+1}^{nt}$	0.535^{***} (0.107)	0.525^{***} (0.113)	0.529^{***} (0.116)
π_{t-1}^{*}	0.047^{***} (0.016)	0.051^{***} (0.016)	0.054^{***} (0.016)
$\hat{\chi}_{t-j}$	-0.310^{*} (0.184)	0.104 (0.078)	0.054 (0.065)
de_t	0.811^{***} (0.176)	0.772^{***} (0.176)	0.758^{***} (0.164)
$shtr_{t-1}$	0.045^{**} (0.020)	0.032^{*} (0.016)	0.032^{**} (0.016)
$\log\left(\sigma_{fr}^2\right)$	-10.350^{***} (0.252)	-10.327^{***} (0.229)	-10.294^{***} (0.214)
Log-likelihood	199.073	198.449	197.587

Note: Sample: 1999Q3 – 2012Q4
Parenthesis: st. dev.; Signif.: $*\,(10\%)$, $**\,(5\%)$, $***\,(1\%)$
M_1: $\hat{\chi}_{t-j} = \hat{u}_t$
M_2: $\hat{\chi}_{t-j} = \hat{c}_{t-2}$
M_3: $\hat{\chi}_{t-j} = \hat{y}_{t-3}$

These results confirm what is found in the literature. Some economists have reported difficulties in obtaining significant parameters for the unemployment gap when estimating aggregate Phillips curves, which could suggest a weak (or nonexistent) relationship between inflation and unemployment in the short run (e.g. Mendonca et al. (2012), Delfim Netto (2013) and Minella et al. (2003)). In section 4.4, we show how model M_1 improves by using the method we propose in this paper.

Following, the two disaggregated specifications are estimated. In model M_S, NAIRU and NAICU are estimated directly as the latent variables in the Kalman filter. Model M_A uses the recursive procedure described above, with initial auxiliary variables for the NAIRU and NAICU obtained by HP_{1600} filtering. The state variables in this model are the deviations of the initial trajectories.

The estimation results of the two models are reported in Table 2. We also present the results of the first step of the recursive estimation of model M_A, i.e., the step in which the gaps are simply those obtained by HP filtering: $\hat{u}_t^{hp} \equiv u_t - u_t^{hp}$ and $\hat{c}_t^{hp} \equiv c_t - c_t^{hp}$. We call this specification as model M_0.[14] The first worth mentioning result concerns the unemployment gap in the Phillips curve of non-traded goods. Not only the coefficients are very significant in models M_A and M_S, as their magnitudes are large (-0.31 in both models). This result suggests that the labor market plays an important role in inflation dynamics: reductions in unemployment below the NAIRU directly affect the inflation rate of non-traded goods and, consequently, the aggregate inflation rate.[15]

That is an indication that the difficulties in finding significant parameters for the unemployment in the Phillips curve may arise from the approach used by the authors to capture this relationship. The evidence provided by the aggregate counterfactual model is reinforced by model M_0, which suggests that simply using the HP-filtered unemployment gap, without considering any economic structure such as the ones we impose in the Kalman filter in this paper, seems not to be a good strategy.[16] Indeed, the coefficient estimated in model M_0 is much smaller (-0.17) than those obtained in models M_A and M_S and is not statistically significant (P-value equal to 0.21). This fact is a strong

[14] The estimation for 2002Q2-2012Q4 is reported in Table 4 in the appendix. In general, the results are pretty similar.

[15] This result complements those found in Banco Central do Brasil (2013), although that study considers wages instead of the unemployment gap.

[16] Mendonca et al. (2012) use both the unemployment gap, obtained by HP filtering, and the actual unemployment rate in various specifications of the Phillips curve. Their results suggest that, although very small, the relationship between inflation and unemployment in Brazil exists in the short run.

evidence that the HP-filtered unemployment gap has measurement errors. It is a well-known result in the econometric literature that an attenuation bias towards zero arises when a regressor has measurement errors (e.g. Wooldridge (2010, cap. 4)).

Table 2: Estimated Parameters

	M_S	M_0	M_A
Phillips Curve: Non-Traded Goods			
π^{fr}_{t-1}	0.367*** (0.065)	0.358*** (0.079)	0.357*** (0.066)
$E_t\pi^{nt}_{t+1}$	0.609*** (0.063)	0.618*** (0.081)	0.619*** (0.064)
π^{*}_{t-1}	0.024** (0.012)	0.024* (0.014)	0.024** (0.012)
$\hat{u}^{hp}_t$ or $\hat{u}_t$	−0.306*** (0.067)	$\boxed{-0.166}$ (0.131)	−0.314*** (0.066)
de_t	0.380*** (0.124)	0.373*** (0.140)	0.371*** (0.127)
Phillips Curve: Traded Goods			
π^{fr}_{t-1}	0.445*** (0.121)	0.436*** (0.126)	0.446*** (0.121)
$E_t\pi^{tr}_{t+1}$	0.485*** (0.118)	0.493*** (0.123)	0.484*** (0.117)
π^{*}_{t-1}	0.070*** (0.016)	0.072*** (0.017)	0.070*** (0.016)
$\hat{c}^{hp}_{t-2}$ or $\hat{c}_{t-2}$	0.145*** (0.049)	$\boxed{0.148^{*}}$ (0.087)	0.145*** (0.049)
de_t	1.154*** (0.240)	1.155*** (0.250)	1.156*** (0.242)
$shtr_{t-1}$	0.068*** (0.017)	0.069*** (0.022)	0.068*** (0.017)
$\log(\sigma^2_{nt})$	−11.250*** (0.258)	−10.973*** (0.340)	−11.261*** (0.256)
$\log(\sigma^2_{tr})$	−9.434*** (0.654)	−9.404*** (0.575)	−9.435*** (0.660)
$\log(\sigma^2_{fr})$	−10.419*** (0.714)	−10.389*** (0.717)	−10.423*** (0.705)
$\log(\sigma^2_{d})$	−14.977*** (0.714)	-	−14.977*** (0.714)
Log-likelihood Step 1	597.850	589.007	598.298
Log-likelihood Step 2	535.666	-	536.794

Note: Sample: 1999Q3 – 2012Q4
Parenthesis: st. dev.; Signif.: $*\,(10\%)$, $**\,(5\%)$, $***\,(1\%)$
M_0: step 1, iteration 1, HP_{1600} filtering with initial values for NAIRU and NAICU, no corrections
M_A: corrections for NAIRU and NAICU inferred by Kalman filtering using auxiliary series (HP_{1600})
M_S: NAIRU and NAICU inferred by Kalman filtering

The estimated coefficients for the capacity utilization gap in models M_A and M_S (both equal to 0.15) are also very significant, indicating that this variable plays as well an important role in inflation dynamics. Note, however, that if we have considered only the HP-filtered gap (model M_0) the estimated coefficient would be significant only at the

10% level. The central estimate would be about the same as the ones obtained in models M_A and M_S. This suggests that the dynamics obtained by Kalman filtering is more consistent with inflation dynamics, even though both the Kalman filter and HP-filtered capacity utilization gaps have similar average volatilities.

As for the other estimated coefficients in models M_A and M_S, most are statistically significant and have theoretically expected signs. Commodity shocks and changes in relative prices seem to be important for inflation dynamics. Also worth noting are the magnitudes of the pass-through coefficients, from international to domestic prices, in the Phillips curves of traded and non-traded goods. While the short-run coefficient is estimated at around 7% for traded goods, it is only about 2% for non-traded goods.

Finally, the estimated coefficient on inflation inertia of non-traded goods ($\lambda_1 = 0.36$) is smaller than that of inflation of traded goods ($\gamma_1 = 0.45$). This is not an expected result for Brazil due to the existence of indexation rules for readjusting part of wages in the sector of non-traded goods. However, a Wald test is not able to reject the null of $\lambda_1 = \gamma_1$.

4.1 Comparing the models

The evidence shown in the previous section suggests that HP-filtered gaps may have measurement errors, which generate difficulties in estimating the relationship between unemployment, capacity utilization and inflation. Therefore, we expect model M_0 to be inferior to the other two. In fact, its log-likelihood is much smaller than the log-likelihoods of models M_A and M_S.[17] Indeed, differences greater than $\log(100) = 4.60$ are very large and can be interpreted as decisive evidence against model M_0 compared to M_A or M_S.[18]

The difference between M_A and M_S is more tenuous, since their log-likelihood values are quite close. Using Kass and Raftery (1995) criterion, model M_A has is a slightly advantage over M_S. Moreover, convergence of the iterative process is faster when using model M_A. Therefore, we choose this specification as our benchmark model.

[17] A more precise analysis requires the use of marginal log-likelihoods. However, the fact that the confidence intervals of the coefficient on the unemployment gap are much narrower in models M_A and M_S than in model M_0 suggests that this criterion would provide the same conclusion.

[18] This decision rule is described in Kass and Raftery (1995) and is based on Jeffreys (1961) suggestions.

4.2 Non-accelerating inflation rates

Now we present our estimates of NAIRU and NAICU using the benchmark model M_A.[19] Panels (A) and (B) of Figure 2 show the NAIRU and NAICU (smoothed series) for 2001Q1 to 2012Q4,[20] the unemployment and capacity utilization rates, and their HP-filtered series. Panels (C) and (D) show 95% confidence intervals (smoothed series).

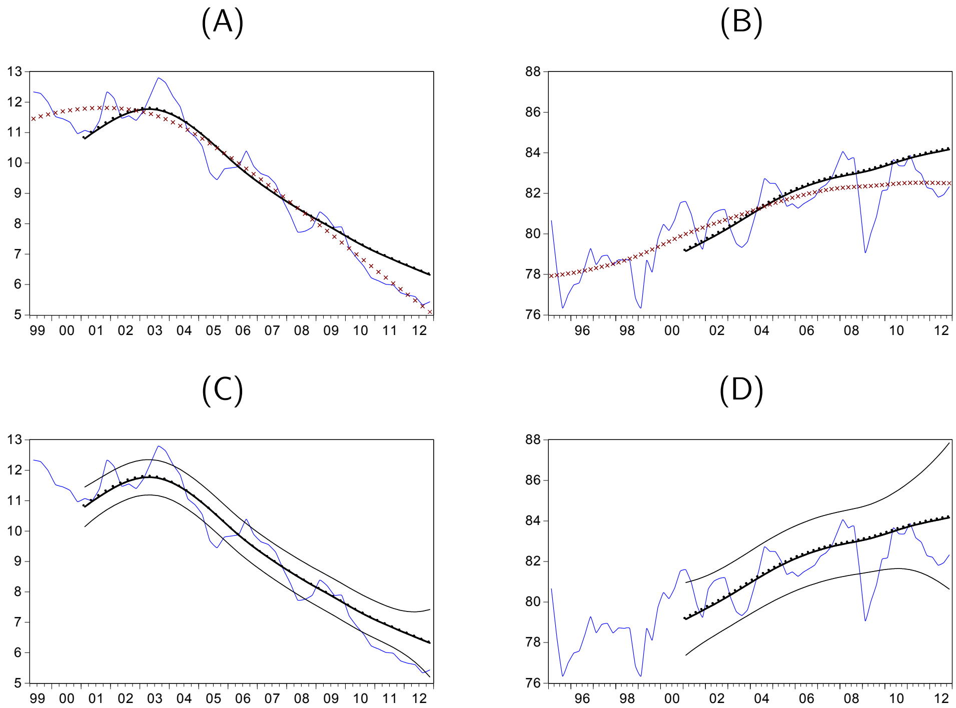

Figure 2: NAIRU and NAICU, benchmark model

Note: Panel (A): Unemployment rate (blue), NAIRU (black circles), HP trend (red stars).
Panel (B): Capacity utilization (blue), NAICU (black circles), HP trend (red stars).
Panel (C): Unemployment rate (blue), NAIRU (black circles), 95% confidence interval (black).
Panel (D): Capacity utilization (blue), NAICU (black circles), 95% confidence interval (black).

The results suggest that NAIRU has substantially decreased in Brazil over the last years. The estimates indicate that while it was close to 11–12% at the beginning of the

[19] The estimates of NAIRU and NAICU using model M_S, as well as an alternative estimation of model M_A using the sub-sample 2002Q2-2012Q4, are depicted in Figures 4 e 5 in the appendix. The results, however, seem not to change much.

[20] The model was estimated using data from the 1999Q3 to 2012Q4. However, we discard the initial values because inferring the states in the initial periods is subject to errors of the initial distribution used by the Kalman filter.

sample, it has decreased to something close to 6.3% in late 2012.[21] Our central estimates suggest that the unemployment rate has been below the NAIRU since mid-2010.

Our estimates also suggest that the actual capacity utilization rate has been well below the NAICU in recent years, despite the fact that both the level of capacity utilization and the NAICU have overall increasing trends in the sample.

As in any inference of latent variables, however, our central estimates of NAIRU and NAICU have a high degree of uncertainty (as suggested by the confidence interval shown in Panels (C) and (D)) and should be interpreted with care.

da Silva Filho (2008), using data from 1996Q2–2006Q4, finds evidence of a constant NAIRU (ranging at 7.4–8.5%), but highlights the fact that his estimates are quite sensitive to including or not proxies to supply shocks in the Phillips curve.

Note that our estimates are consistent with da Silva Filho (2008) in the 2001Q1–2006Q4 period, for our central estimates show relatively little variation given the confidence intervals: it starts at about 11% by 2001, slightly increases to 12% in mid-2003, and returns to about 10% in late 2006. Indeed, we can not reject the null that the NAIRU has effectively remained constant until the end of 2006. However, when considering the whole sample, the evidence suggests that the NAIRU has significantly decreased in Brazil. In a recent extension (covering March 2002 to March 2011), da Silva Filho (2012) estimates a larger, but still constant, level for the NAIRU (9.6%). This result, however, is difficult to be reconciled with our estimates.

Additionally, there are important differences between our estimated paths for the NAIRU and NAICU and those obtained using HP filtering. Our NAIRU estimates and the HP trend are quite similar over 2003 to 2008. Nevertheless, our beginning-of-sample estimates are smaller than HP ones (our NAIRU estimates oscillate around 11.3%, whereas the HP trend oscillates around 12% before 2002Q4), and the opposite happens at the sample end (our NAIRU estimates oscillate around 6.7%, whereas the HP trend oscillates around 5.8% from 2011Q1 to 2012Q4). In the NAICU case, we also observe important end-of-sample differences. From 2011Q1 to 2012Q4, our NAICU estimates average 84.0%, whereas the HP trend oscillates around 82.5%.

There is an important message from those results. In line with recently observed

[21] There are few studies with updated data on NAIRU in Brazil. The two most recent estimates are found in da Silva Filho (2008, 2012). Older analyses are found in e.g. Portugal and Madalozzo (2000) and Lima (2003).

larger inflation rates for non-traded goods, our estimated NAIRU indicates that the labor market is tighter in recent years than what is suggested by HP filtering. On the other hand, also consistent with smaller inflation rates for traded goods, our estimated NAICU suggests that the manufacturing sector has been operating in a more sluggish way than what is suggested by HP filtering.[22]

4.3 The three gaps

In this section, we describe how to retrieve an aggregate measure of output gap using our estimates for the NAIRU and NAICU. We assume that GDP, Y_t, is produced according to a Cobb-Douglas technology, $Y_t = A_t \left(K_t C_t\right)^{1-\alpha} \left[L_t \left(1 - U_t\right)\right]^{\alpha}$, where A_t is the exogenous technology shock, K_t is the capital stock, C_t stands for capacity utilization, L_t is the labor force, U_t is the unemployment rate, and $\alpha = 0.67$, as estimated in Gomes et al. (2005). The potential output is given by $Y_t^n = A_t \left(K_t C_t^n\right)^{1-\alpha} \left[L_t \left(1 - U_t^n\right)\right]^{\alpha}$, where C_t^n is the NAICU and U_t^n is the NAIRU.

Our assumptions give us a simple way to compute the (gross) output gap, Y_t/Y_t^n, without relying on inferring the labor force, capital stock or the technology shock: $\frac{Y_t}{Y_t^n} = \left(\frac{C_t}{C_t^n}\right)^{1-\alpha} \left(\frac{1-U_t}{1-U_t^n}\right)^{\alpha}$. In log-notation, we have:

$$\hat{y}_t = \left(1 - \alpha\right) \hat{c}_t + \alpha \hat{e}_t = \left(1 - \alpha\right) \hat{c}_t - \alpha \hat{u}_t, \tag{8}$$

where $\hat{y}_t$ is the output gap, $\hat{c}_t$ is the capacity utilization gap, $\hat{u}_t$ is the unemployment gap and $\hat{e}_t \simeq -\hat{u}_t$ is the employment gap. Therefore, the output gap is a combination of the capacity utilization and employment gaps.

Panel (A) of Figure 3 shows the three gaps: the employment gap, the capacity utilization gap and output gap. Panel (B) compares the estimated output gap with the one obtained by using HP-filtering for extracting the GDP trend. Panels (C) and (D) compare, respectively, our estimates of the capacity utilization and employment gaps with HP-filtered gaps.

Figure 3 summarizes our main findings: (i) even though suggesting an economic slowdown by the end of 2012, our estimates for the output gap clearly suggests that the

[22] The differences stem from the fact that our approach takes into account the interaction between the inflation rates of traded and non-traded goods when estimating the NAIRU and NAICU, while HP filtering is just a low-pass filter with no economic reasoning.

Brazilian economy was better than what is implied by simply HP-filtering the GDP time series (Panel (B)); (*ii*) by the same period, our estimates suggest that the manufacturing sector was more sluggish than what HP-filtering implies (Panel (C)); and (*iii*), on the other hand, we find evidence that the labor market was more heated than what predicted by HP-filtering (Panel (D)).

Both measures of output gap display similar dynamics throughout the sample, as shown in Panel (B). However, the HP-filter gap has more pronounced movements, especially after 2007. From the world economic crisis of 2007/2008 on, the HP gap measure became extremely volatile, whereas our measure remained with the same volatility level as before the crisis.

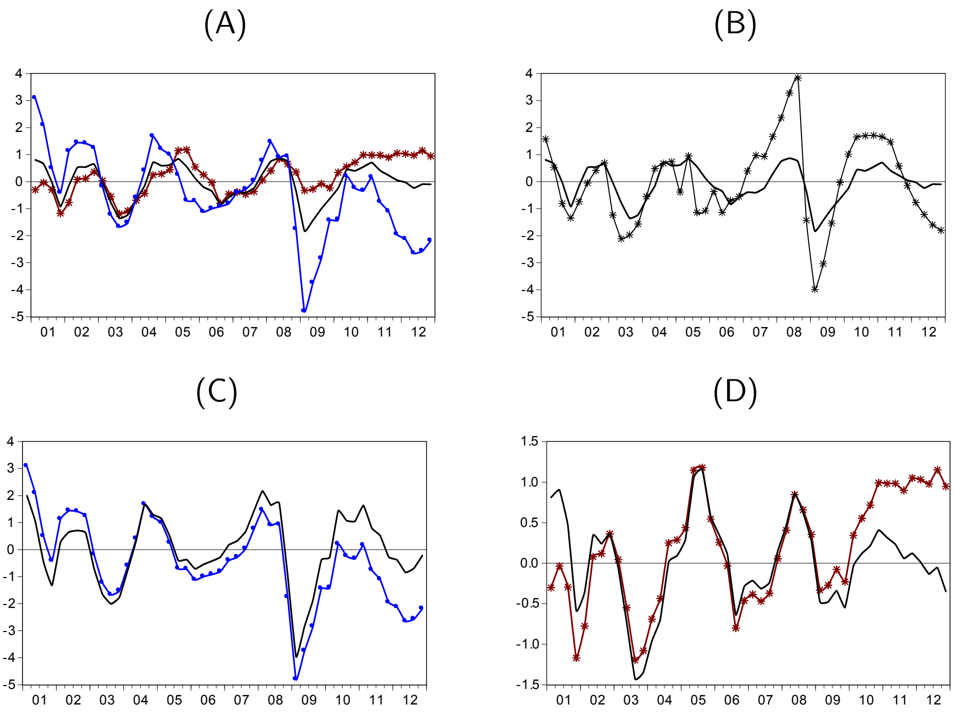

Figure 3: Gaps

Note: Panel (A): Employment gap (red stars), Capacity utilization gap (blue circles), Output gap (black).
Panel (B): Output gap (black), Quasi GDP gap obtained by HP_{1600} filtering (black stars).
Panel (C): Capacity utilization gap (blue circles), Quasi Capacity utilization gap obtained by HP_{1600} filtering (black).
Panel (D): Employment gap (red stars), Quasi Employment gap obtained by HP_{1600} filtering (black).

4.4 Improved aggregate model

We also apply our method to the aggregate model. Since the specification with the unemployment gap outperformed the remaining specifications, i.e. with capacity utilization and GDP gaps, we ilustrate the gains obtained from applying it to the model M_1. Table 3 shows the results.

Table 3: Aggregate Model - Estimated Parameters

	M_1^s	M_1	M_1^A
Aggregate Phillips Curve			
π_{t-1}^{fr}	0.285^{***}	0.417^{***}	0.274^{***}
	(0.090)	(0.109)	(0.090)
$E_t\pi_{t+1}^{nt}$	0.680^{***}	0.535^{***}	0.691^{***}
	(0.092)	(0.107)	(0.091)
π_{t-1}^{*}	0.035^{***}	0.047^{***}	0.034^{***}
	(0.013)	(0.016)	(0.013)
$\hat{u}_t$	-0.585^{***}	$\boxed{-0.310^{*}}$	-0.589^{***}
	(0.172)	$\boxed{(0.184)}$	(0.169)
de_t	0.807^{***}	0.811^{***}	0.802^{***}
	(0.137)	(0.176)	(0.138)
$shtr_{t-1}$	0.060^{***}	0.045^{**}	0.061^{***}
	(0.014)	(0.020)	(0.014)
$\log\left(\sigma_{fr}^2\right)$	-10.526^{***}	-10.350^{***}	-10.534^{***}
	(0.216)	(0.252)	(0.213)
$\log\left(\sigma_d^2\right)$	-14.417^{***}	-	-14.417^{***}
	(1.053)		(1.053)
Log-likelihood Step 1	203.732	198.449	203.934
Log-likelihood Step 2	166.204	-	166.963

Note: Sample: 1999Q3 – 2012Q4
Parenthesis: st. dev.; Signif.: $*$ (10%), $**$ (5%), $***$ (1%)
M_1: step 1, iteration 1, HP_{1600} filtering for NAIRU
M_1^A: corrections for NAIRU inferred by Kalman filtering using auxiliary series (HP_{1600})
M_1^S: NAIRU inferred by Kalman filtering

Qualitatively, the improvement of the aggregate model is the same as the one achieved using the disaggregate model, i.e. the coefficient on the unemployment gap became significant at 1% and its central estimate increased when compared to the one obtained with HP-filtering gap. The latter suggest that the atenuation bias was at play when using HP-filtered gaps, for it does not consider any economic structure. Notice that the magnitrude of the central estimate of the unemployment gap parameter is larger than that obtained in the disagregate model. The reason for this result is that the standard deviation of the aggregate free prices inflation rate is about 60% larger than that of the non-traded inflation rate.

5 Conclusions

Brazil has been experiencing an odd economic instance in recent years. In the aggregate, economists have been facing a hard time to find a positive correlation between employment and inflation, which should be a trivial task in most countries. In our conterfactual exercise, we find similar evidence, when considering an aggregate Phillips curve with either unemployment, capacity utilization or GDP HP-filtered gaps. Hence, a puzzle arises in understanding the lack of such correlation.

In order to solve this puzzle, we have looked into disaggregated measures. In particular, we have explored the dichotomy in the Brazilian economy: Brazil has been characterized by low and decreasing unemployment rates along the last decade, on the one hand, and low capacity utilization and GDP growth rates, on the other hand. Simultaneously, the inflation rate in the sector of non-traded goods has been persistently high in recent years, up to 2012, while the inflation rate in the sector of traded goods has been much lower.

In this context, we have tested a semi-structural empirical model to study the relationship between unemployment, capacity utilization and inflation in Brazil. The key feature of the model is that it has two separate Phillips curves, one for the inflation rate of traded goods and another for the inflation rate of non-traded goods, which are jointly estimated by full-information maximum likelihood method. In the sector of traded goods, we assume that production is much more intensive in capital, whereas it is intensive in labor in the sector of non-traded goods.

Therefore, we assume that the Phillips curves for the sectors of traded and non-traded goods have the capacity utilization gap and the unemployment gap as appropriate demand variables, respectively. We use the Kalman filter to infer the non-accelerating inflation rate of unemployment (NAIRU) and non-accelerating inflation rate of capacity utilization (NAICU), by means of adding economic structure in inference. Using a simple production function, we combine those results to obtain three gaps: unemployment gap, capacity utilization gap and output gap.

Our results suggest that the labor market does have a significant impact on the dynamics of inflation, especially through the non-traded goods sector. The impact of capacity utilization, through inflation of traded goods, is also relevant. We argue that the evidence of a weak relationship between unemployment and inflation in Brazil, reported by many economists, may be due to: (i) standard analyses using aggregate quantities, which disregard the idiosyncrasies of different sectors; and (ii) measurement errors in the variable used as the unemployment gap, obtained by a naive HP-filtering, which cause attenuation biases during inference.

We find that the manufacturing sector is more sluggish than what HP-filtered capacity utilization gaps suggest, whereas the labor market is tighter than what HP-filtered unemployment gaps predict.

Finally, our results emphasize the dichotomy experienced by Brazilian economy. They suggest that the NAIRU has substantially reduced in Brazil in recent years, but not as much as the actual unemployment rate has. Our results also indicate that since mid-2010 the labor market has been operating at full-employment and pushing up the inflation rate of non-traded goods. The estimated NAICU path confirms that the manufacturing sector has been slowing down, and that has been keeping the inflation rate of traded goods at bay.

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A Additional results

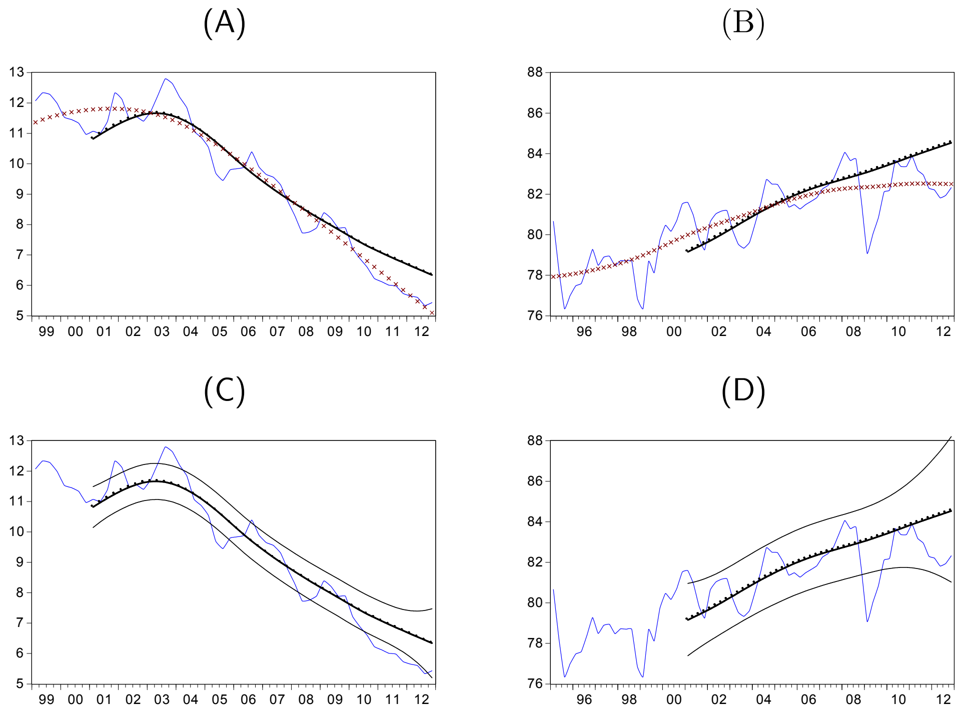

Figure 4: NAIRU and NAICU, standard model

Note: Panel (A): Unemployment rate (blue), NAIRU (black circles), HP trend (red stars).
Panel (B): Capacity utilization (blue), NAICU (black circles), HP trend (red stars).
Panel (C): Unemployment rate (blue), NAIRU (black circles), 95% confidence interval (black).
Panel (D): Capacity utilization (blue), NAICU (black circles), 95% confidence interval (black).

Table 4: Estimated Parameters, sample starting at 2002Q2

	M_0	M_A
Phillips Curve: Non-Traded Goods		
π^{fr}_{t-1}	0.346^{***} (0.101)	0.342^{***} (0.081)
$E_t\pi^{nt}_{t+1}$	0.629^{***} (0.099)	0.634^{***} (0.079)
π^*_{t-1}	0.025 (0.017)	0.024^{*} (0.014)
$\hat{u}^{hp}_t$ or $\hat{u}_t$	$\boxed{-0.234^{*}\ (0.137)}$	-0.288^{***} (0.091)
de_t	0.311^{*} (0.164)	0.314^{**} (0.131)
Phillips Curve: Traded Goods		
π^{fr}_{t-1}	0.492^{***} (0.130)	0.481^{***} (0.125)
$E_t\pi^{tr}_{t+1}$	0.420^{***} (0.128)	0.435^{***} (0.116)
π^*_{t-1}	0.088^{***} (0.017)	0.084^{***} (0.017)
$\hat{c}^{hp}_{t-2}$ or $\hat{c}_{t-2}$	$\boxed{0.151\ (0.095)}$	0.202^{***} (0.058)
de_t	0.966^{***} (0.242)	0.935^{***} (0.227)
$shtr_{t-1}$	0.046^{**} (0.025)	0.041^{***} (0.014)
$\log(\sigma^2_{nt})$	-11.054^{***} (0.397)	-11.222^{***} (0.346)
$\log(\sigma^2_{tr})$	-9.639^{***} (0.546)	-9.743^{***} (0.576)
$\log(\sigma^2_{fr})$	-10.609^{***} (0.624)	-10.677^{***} (0.653)
$\log(\sigma^2_{d})$	-	-10.657^{***} (0.550)
Log-likelihood Step 1	489.964	497.286
Log-likelihood Step 2		415.871

Nota: Sample: 2002Q2 – 2012Q4
Parenthesis: st. dev.; Signif.: $*\,(10\%)$, $**\,(5\%)$, $***\,(1\%)$
M_0: step 1, iteration 1, HP_{1600} filtering with initial values for NAIRU and NAICU, no corrections
M_A: corrections for NAIRU and NAICU inferred by Kalman filtering using auxiliary series (HP_{1600})

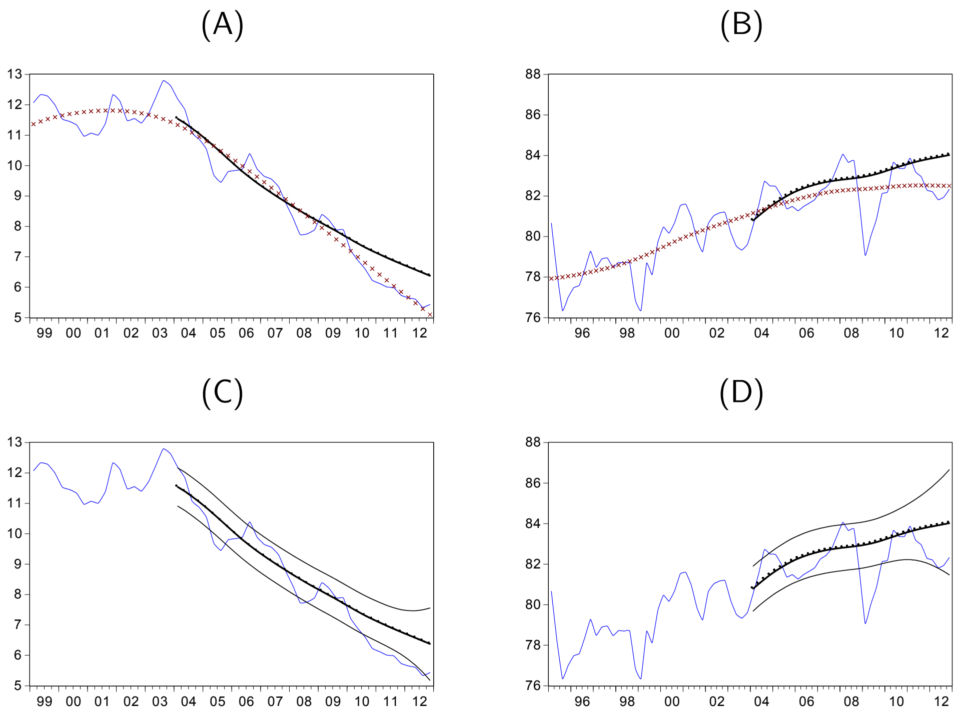

Figure 5: NAIRU and NAICU, benchmark model, sample starting at 2002Q2

Note: Panel (A): Unemployment rate (blue), NAIRU (black circles), HP trend (red stars).
Panel (B): Capacity utilization (blue), NAICU (black circles), HP trend (red stars).
Panel (C): Unemployment rate (blue), NAIRU (black circles), 95% confidence interval (black).
Panel (D): Capacity utilization (blue), NAICU (black circles), 95% confidence interval (black).