Estimating an Output Gap Indicator Using Business Surveys and Real Data

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Abstract

In Colombia's Central Bank various output gap measures are calculated. To improve the analysis, specialists also follow business surveys and real data. Summarizing all the information into one estimation is necessary and problematic. In this paper an output gap indicator is estimated as the unobserved factor from all the alternative measures, using principal components analysis. The quality of the indicator is evaluated by its out-of-sample predictive ability of the core inflation, using a hybrid Phillips Curve. The results suggest that the indicator that excludes the measures from traditional statistical filters is better for identifying demand pressures than any of the individual measures.

Key words: Output gap, principal components, Phillips Curve, Colombia.

JEL: C32, C43, E31, E37, E52.

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I. Introduction

The Central Bank of Colombia conducts monetary policy using Inflation Targeting since 1999, after exchange rate bands were abandoned. Under this regime, the interest rate that is charged to the commercial banks for their overnight liquidity demands depends on the double relation between the expected future inflation and the inflation target, and the GDP and the non inflationary product. Therefore, monetary policy depends critically on inflation forecasts[2], which require a complete real time analysis of the current and future economic situation, using all the disposable information which is always incomplete (Giannone et. al. 2005)[3]. The analysis from the staff at the Central Bank is primarily focused in the transmission mechanisms of monetary policy that are included in the central forecasting model (TMM)[4]: output gap, inflation expectations, the nominal exchange rate and the policy instruments (the target and the overnight rate).

This work explores an alternative estimation of the output gap, defined as the difference between the observed and the non-inflationary GDP[5], in order to improve the inflation forecasts. Since the latter is an unobserved variable it is very difficult to gauge how adequate are the models that are employed for its estimation. The importance of a good calculation is that it signals possible demand pressures that may push prices in the future.

The techniques that are present in the literature are diverse, and even though in principle it may seem adequate to have various measurements which employ distinct methodologies, in practice this implies

[2] López (2004) shows that in Colombia, a policy rule that is based in projections produces better macroeconomic results than the one that only responds to contemporaneous inflation, since the forecasts implicitly respond to various factors.

[3] This process must take into account the uncertainty associated with the lack of knowledge of the “true" model of the economy, the considerable lag in the data publication and their later revisions.

[4] The TMM (*Transmission Mechanisms Model*) developed by Gómez et. al. (2002), is a quarterly, semi-structural, dynamic model for a small open economy, which is actively used for policy recommendations.

[5] In some works the output gap is calculated using the potential GDP (which would prevail if all prices were flexible or if all the production factors were completely used). However, this is not the relevant measurement for a Central Bank under inflation targeting. In practice, the non inflationary GDP is smaller than the one that could be reached if all factors were completely used. A detailed description of alternative definitions for the potential output is presented in McCallum (2001).

different analysis of the current situation and ultimately lead to diverse and possibly opposing policy recommendations. Even though the historical correlation between the measures is usually very high, their levels vary considerably, specially for the latest estimations which are incidentally the most important. In Figure 1 three of the alterative measures for Colombia's output gap that the Inflation staff at the Central Bank monitors regularly are presented along with the maximum and minimum values from all the available measures at each point in time.

(Insert Figure 1 here)

This work proposes principal components analysis as a tool for resuming in only one measure all the disposable information of the demand situation in the economy. Because of the unobservability of the output gap, the validity of all the individual measurements that are currently used and of the new aggregated measures that are proposed, are evaluated by the out of sample forecasts for the core inflation that are produced using these measures as activity indicators in a hybrid Phillips Curve[6].

This work is divided into five sections including this introduction. The second further explains the importance of an alternative measure for the output gap that aggregates the disposable information of possible demand pressures. It also presents the main advantages, disadvantages, applications and alternatives of the technique that is employed. The third section introduces the theory of factor analysis. The fourth explains the estimations and presents the results and the forecast evaluations. Finally, in the fifth section some conclusions are drawn.

II. Theoretical Framework

The potential GDP, though commonly mentioned in the literature is a non-observable vague theoretical concept. Therefore, there is not a perfect measure and as mentioned earlier, the literature is full of estimation methods and strategies. In Colombia the majority of this methods are currently employed,

[6] Such as the one used in the TMM, which includes rational (forward looking of future inflation) and adaptative expectations (based on the lagged inflation).

which range from pure statistical filters (Hodrick Prescott, multivariate Hodrick Prescott, Hodrick Prescott with *priors*, Kalman filter and Band Pass) to more theoretical approaches (production functions and structural VAR's)[7].

A. The aggregation problem

Because of the uncertainty that accompanies any estimation of demand pressures, the staff at the Central Bank usually completes the analysis with information from different sources, coming from specific sectors and from surveys, which help in the process of creating a coherent assessment of the demand situation. It is therefore desirable to have a formal tool that is flexible enough to incorporate real-time information from different sources and can conciliate different signals that may arise from the indicators.

Aggregating data is usually very complex in economics, but in this setting it is specially difficult because of the differences in the frequencies of the data (daily, monthly, quarterly or annual), in the units of measurement (nominal, real, balances, indexes), in the lags of data releases, in the informational content and in the degree of aggregation. Nonetheless, these difficulties should by no means lead the specialists to discard valuable pieces of information or to assign them little weight in their assessment, since all of them could potentially provide additional information of the demand situation in the economy.

Unfortunately, in many cases even though the analysts understand the potential bias in which they incur by ignoring information, they can do no better due to the absence of an objective scheme that helps them use efficiently all the available data. The arbitrary selection of some of the data for a certain forecasting model may lead to an omitted variable problem, which worsens its performance (Bernanke y Boivin 2003). Because of this, it is possible to argue that the analysis could be improved if all the available information is adequately used. However, choosing some few variables from the available data is obligatory for the estimation of traditional econometric models, due to the impossibility of estimating a model where the number of explanatory variables exceeds the number of observations because of the

[7] Cobo (2004) presents an exhaustive review of the different methodologies that have been applied in Colombia.

lack of degrees of freedom.

These problems that convey the use of the available information necessarily increase the uncertainty on any measure of demand pressures. Which ultimately leads policy makers to procrastinate interest rate moves until most of the variables signal the same risks, therefore loosing the lead that some of the indicators may have over others[8]. This additional time may be costly since policy makers may need additional policy moves if they find that they are *falling behind the curve*, which could be avoided with small but early actions.

B. Principal components as an aggregation method

One way of overcoming these problems, is to aggregate information from different sources in the way the NBER started doing it more than fifty years ago. Their diffusion indexes are a weighted average of all available contemporaneous information. Where the weights change slowly in time and are assigned by expert judgment. This way the aggregation problem is covered, however the arbitrary selection of the weights does not solve the possible bias caused by the omission of relevant information.

This work proposes Principal Components Analysis (PCA) as an alternative for aggregating all the disposable information on output gap and inflation pressures. This procedure decomposes the original series into a common factor (which summarizes the co-movements of all the series and should thereby reflect the *fundamentals*) and specific shocks (capturing possible measurement errors and data revisions). Bernanke and Boivin (2003) show that the estimated factors by PCA are an efficient summary of the information contained in a great variety of series and that in this way the forecasting models get closer to reality, by using a great amount of the disposable series in real time. In this way the aggregation problem is covered, and the possible discretional bias is also minimized since the weights come from the data and not from the judgment of the staff.

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[8] In Colombia, as in other countries, it is well known that the labor market typically lags the results of the rest of the economy. Therefore waiting for the unemployment to get to a certain level before taking any decision, may not be the best strategy for policymakers.

Stock and Watson (2004) mention that by using PCA the problem of selecting some variables for a model is extremely reduced, since all of the possible predictors are replaced by a few factors which contain the majority of the information from the original variables. Allowing the estimation of models where the number of predictors is greater than the number of observations, thereby changing the curse of having too much available information into a blessing.

Several authors have extensively demonstrated that the forecast errors of the models that include estimated factors tend to be smaller than those of traditional models[9]. Since by exploiting more efficiently the available information, not only the omitted variable problem is alleviated, but also the structural instability that plagues low dimensional estimations is lessened. For example, Stock and Watson (1999) prove that a generalized Phillips Curve, which includes an estimated factor from many series, presents less instability in the estimated parameters and produces better inflation forecasts than those which only include one activity measure[10].

According to Fisher (2000), the main advantage of factor models to forecast inflation, is that prices are determined through a complex interaction of many variables, which are also unstable through time and are affected by the Lucas critique. Which explains why a certain variable may be very useful to forecast inflation at one point in time, but when the economy changes other turns out to be more important. Therefore, a model which accurately includes a summary of all the potentially relevant variables should produce more stable and reliable forecasts.

According to Bernanke and Boivin (2003), PCA is especially useful for monetary policy analyzes because it is rigorous but flexible enough to permit the use of information in different formats. They also point that the method does not impose any economic structure and solves in a simple and efficient manner the

[9] Some of the most important are: Stock et. al. (1999, 2002 and 2004) and Giannone et. al. (2004).

[10] Several authors have proved the empirical instability of the Phillips Curve and commented its potential causes and consequences. Two examples are: Deutsche Bank (2005) for the US and King (2005) for the UK.

main problems of the low dimensional forecast models that are traditionally used[11]. Another powerful advantage of the method is that by separating the series into their common and autonomous part, the quality of the estimations is not affected if preliminary data is used. Which results from the fact that data revisions and measurement errors are not be correlated among the series[12].

Despite all the benefits that have been mentioned, using PCA to estimate an output gap indicator has some problems. The first one is that the results are very dependent on the quality and variety of the disposable information used to calculate the factor. Therefore, the initial selection of variables is not innocuous as verified by Boivin and Ng (2003) using Monte Carlo simulations. However, there is not a formal rule about the number and the type of variables that are needed for an adequate estimation of the factor. For example, Watson (2000) shows that for the US data, augmenting the number of series beyond fifty does not have a significant effect in forecast errors[13].

The common factors may also be estimated using the dynamic methodology in stages developed by Forni, et. al., (2000)[14]. Their procedure is based in the frequency domain analysis and its main objective is the estimation of the common component of the series and not of each factor. In theory, it should be superior to the static methodology (PCA) since the latter plainly ignores dynamics that may exist within the factors, while the dynamic methodology is specially designed to capture them[15]. However, nothing guarantees that such dynamics may exist and in practice if they do not exist in the data, the dynamic estimation conveys an unnecessary loss in efficiency.

Even though in principle both methodologies can estimate consistently the static and dynamic factorial

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[11] The PCA is non-parametric since the structure of correlation between the variables and the distribution of the factors and the errors are not directly specified.

[12] For the same reason, the method does not suffer too much from the end of sample bias of traditional statistical filters.

[13] Even though having more data is always better according to asymptotic theory, in practice, using data with large measurement errors and with shocks which are highly autocorrelated does not improve the estimation and in the limit can deteriorate the estimation of the common component.

[14] Some older dynamic alternatives are Sargent and Sims (1977) and Geweke (1977).

[15] For example, the static estimation may incorrectly suggest that a particular series is determined by two common independent factors, while the dynamic methodology could capture that the series is only determined by one independent factor and a certain lag of the same factor. However for forecasting purposes, identifying this may not be very useful.

space respectively, there are some important differences in their implementation. For the dynamic estimation, the user must specify in advance the number of dynamic factors, the number of lags of each factor and the number of autocovariances that should be considered for constructing the spectral density matrix and for how many domain frequencies the proper dynamic values (*eigenvalues*) will be estimated[16].

In practice this restrictions are problematic, since the analysts never know the true dynamics of the data generating process. Kapetanios and Marcellino (2003) prove with Monte Carlo simulations that for simple processes both methodologies can adequately estimate the factors. However, when the processes get more complicated the factors estimated with the dynamic methodology have a lower correlation with the real factors than the ones estimated with the static methodology. They also found that the dynamic factors consistently present higher serial correlation and smaller variance in the idiosyncratic component. Which are clear signs of *overfitting*, as the estimation tends to include a fraction of the idiosyncratic errors as part of the common component[17]. Since the dynamic methodology is more complicated and is by no means superior to its static counterpart, we decided to discard the former and concentrate in the latter for this work.

C. Recent applications of factor models

Factor models have recently had a wide variety of applications in diverse areas. Some examples are the European coincident activity index (Eurocoin)[18], the economic activity index of the Chicago FED (CFNAI) [19], forecasts of the returns of treasury bonds[20], the estimation of inputs for dynamic general equilibrium

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[16] The estimated dynamic factors are obtained from a proper value decomposition of the smoothed spectrum for various frequencies and the static factors come from the matrix of sample covariances.

[17] This is why a high R^2 is not enough to know if the estimated factor truly summarizes the information from the series.

[18] Calculated by the Center for Economic Policy Research (CEPR), using dynamic principal components based on the work of Altísimo et. al. (2001).

[19] Using PCA following Stock et. al. (1999)

[20] Ludvigson and Ng (2005) using estimated components with PCA from financial and activity variables.

models[21] and the study of the macroeconomic comovements of the G-7 countries[22]. In Colombia Nieto and Melo (2001) developed a modification to the Stock and Watson (1989 and 1991) methodology, which allows for cointegration and seasonal unit roots in the series. They estimate, using the Kalman Filter, a coincident activity index as the dynamic factor from the state space representation of nine monthly series of activity.

Factor analysis has also had recent applications related to monetary policy, such as Favero et. al. (2005) and Stock and Watson (1999). The former show, using data for Europe and the US that by including estimated factors in Taylor rules uncertainty in the estimated parameters is reduced and more plausible values are obtained. They also find that by including estimated factors in VAR analysis of the transmission mechanism of monetary policy the *price puzzle*[23] is solved and the response of the output gap changes to the right sign. Stock and Watson (1999) use a generalized Phillips Curve to forecast inflation in the US employing various activity *proxies*. They find that the forecasts that are based in estimated factors with PCA from various activity measures are better in terms of forecast errors than the ones based in just one of the measures or on purely autoregressive models.

III. The Methodology: Principal Components Analysis

The purpose of PCA is to obtain a small amount of linear combinations of the original variables, which retain the maximum amount of information from them as is possible. Rigorously the factors[24] are orthogonal (uncorrelated) weighted averages of the original variables, where the first principal component (PC) has greater explanatory power of the variance of the system than any other combination of the

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[21] Boivin and Giannoni (2005) which use dynamic factor analysis.

[22] Kose et. al. (2005), using a dynamic Bayesian model of latent factors.

[23] In this type of works it is common to find that inflation initially rises after an increase in the interest rates, which is obviously counterintuitive. Traditionally this anomaly has been explained as an omitted variable problem, specially of some sort of supply shock. Therefore, using an estimated factor that includes a summary of a wide range of explanatory variables tends to solve this problem.

[24] In this document the terms factor and principal component are freely exchanged, however in a rigorous statistical setting they may not necessarily be equivalent.

observed variables. The first j PC's are also the best predictors of the original variables among all the possible sets of j variables, even though any linear transformation of the first j PC's will produce comparable forecasts.

Given a set of N numeric variables, it is possible to estimate up to N PC's, where each PC is a linear combination of the original variables, with the weights equal to the proper values (eigenvalues) of the correlation matrix of the original variables. The assumption of the estimation is that all series are jointly determined by a small set of common factors and individual (idiosyncratic) shocks. If there are T time series for N cross sectional units denoted $x_{i,t}(i=1...N, t=1...T)$ the static factor model is defined as follows:

(1) $$x_{i,t} = \lambda_{i,1} f_{1,t} + ... + \lambda_{i,r} f_{r,t} + e_{i,t} = \Lambda_i^{'} F_t + e_{it}$$

Where $x_{i,t}$ are observed variables, F_t is a vector of r common factors, Λ_i is the $r \times 1$ vector of coefficients for unit i and $e_{i,t}$ is the idiosyncratic error of the estimation. In principle it is possible to obtain as many factors as variables are considered ($r = N$), but in general only the first $r < N$ factors are needed to explain a big fraction of the total variance of the system.

The ($f_{i,t}$) factors are generally estimated in order to employ them for the estimation of a variable Y_t, using a linear model such as (2):

(2) $$Y_{t+1} = \partial_1(L) f_{1,t} + ... + \partial_q(L) f_{q,t} + \Gamma(L)' Z_t + u_{t+1} = \Delta(L) F_t + \Gamma(L)' Z_t + u_{t+1},$$

Where $\partial_i(L)$, $\Delta(L)$ and $\Gamma(L)$ are functions of the lag operator L, and Z_t is a vector of exogenous variables that may contain lags of Y_t. In the case that u_t (the forecast error of the endogenous variable) presents serial autocorrelation, only the first q of the r factors that determine $x_{i,t}$ are necessary to forecast Y_{t+1} adequately. This model is said to be an approximate factor model representation, since it allows for $e_{i,t}$ having some cross section correlation[25].

Since the common factors are not directly observable they must be estimated using factor analysis, where each of the estimated factors F_t is a linear combination of the elements of vector $x_t = (x_{1,t}...x_{N,t})'$ of dimensions $N \times 1$ and the combination is chosen from the optimization that minimizes the sum of the squares of the residuals $\left(x_{i,t} - \lambda_i f_{i,t}\right)^2$. More over, the estimators of $\hat{F}_t$ must minimize the objective function (3):

$$V_{N,T}(F,\Lambda) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{i,t} - \lambda_i f_{i,t})^2 \tag{3}$$

Under the assumption that there are r common factors, the optimal estimators of the factors turn to be the r proper vectors (eigenvectors) associated to the biggest proper values of matrix $N^{-1}\sum_{i=1}^{N} x_i{}' x_i$ with dimension $T \times T$, that correspond to the principal components of x_t.

Bai and Ng (2005) demonstrate that when $N,T \to \infty$ where $\sqrt{T}/N \to 0$ the coefficients estimated in (2) by OLS are consistent at a speed $\sqrt{T}$, asymptotically normal and that the error of the forecast h periods ahead depends primarily on the variance of the error term (as if F_t was observed). However, it is worthwhile stressing the importance of N being sufficiently large, otherwise it is impossible to estimate consistently the factorial space regardless of the number of observations[26].

In order to choose the number of q factors of that must be used to forecast Y_{t+1}, Stock and Watson

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[25] According to Stock (2004), when working with economic series, is a big advantage of this model over the exact factor model that is estimated with the Kalman Filter.

[26] Since the estimator depends critically on the convergence of the sample covariance matrix to the population covariance matrix of $x_{i,t}$.

(1998) suggest minimizing an information criterion such as the BIC, which performs adequately in their simulations. More recently Bai and Ng (2000) developed a criterion which behaves better for this type of exercises and has rapidly become common in the literature in this kind of exercises. In this paper only the first estimated factor and some of its lags are employed for forecasting purposes[27]. The lags were strategically chosen to minimize the mean square error of the forecasts.

IV. Estimating an Output Gap Indicator with PCA

Giannone et. al. (2005) mention that the information used to forecast in real time should have two desirable characteristics in order to be relevant: it should be published with a minimum lag and it should have a high predictive power. Unfortunately, the series that are more aggregated and therefore have a higher predictive power (hard data) are the ones that are published with the longest lag. The analyst must optimize this tradeoff in real time information and choose series with good predictive power but published with a small lag. Because of this, surveys which are considered as soft data for their supposedly low predictive power and informational content are very important for analysts since they are published with a minimum lag and are not revised[28].

A. The output gap measures used for the estimation

Bearing this tradeoff in mind, we employed for the estimation of the output gap indicator twenty three output gap measures or *proxies*, which are periodically followed by the inflation staff at Colombia's Central Bank and are resumed in Table 1[29]. In order to have a balanced panel, the data set goes from March 1990 to March 2006. The measures and *proxies* employed are:

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[27] Since in $x_{i,t}$ only alternative measures of the output gap are included, it does not make sense to choose more than one factor. The problem of choosing the correct number of factors would be relevant only if nominal, real and financial variables were being used.

[28]For example, Giannone et. al. (2005) found that for US data that in a given quarter when the preliminary activity measures are published, the marginal information that they add to the analysts is minimal since they are published with a three month lag and are subject to revisions in the following quarters.

[29] Some references for this measures are Julio (2001), Cobo (2004), Nigrinis (2003), López and Misas (1998), González et. al. (2006) and Echavarría et. al. (2006).

I. Dd_ANDI: the percentage of entrepreneurs who answer in a survey conducted by the National Association of Industrials (ANDI) that the main problem for their business is the lack of demand in the economy.

II. CU_ANDI: the average percentage of capacity utilization reported in another question of the ANDI survey.

III. Tr_B: trade balance in dollars as measured by the National Department of Statistics (DANE).

IV. Extra_H: index of extra hours worked in the industry as reported in the industrial monthly survey conducted by DANE.

V. Cap vs. Dd: the balance between the percentage of entrepreneurs who answer that their installed capacity is enough to serve their expected demand over the next twelve months and the percentage of those who think it is not enough. As reported in a monthly industry survey conducted by Fedesarrollo which is a major think-tank in Colombia.

VI. CU_FEDE: capacity utilization in the industry as reported in the same monthly survey to Fedesarrollo.

VII. % CU > Av: the percentage of businesses that report in the same survey that their capacity utilization is above its historical average.

VIII. Net_Ext_Dd: the net external demand in constant Colombian pesos of 1994 as measured by DANE in the national accounts.

IX. Lics: the square meters approved in construction licenses as measured by DANE.

X. Ret_Sal: the balance between those who answer that the retail sales from the past month were better (compared to the same month a year ago) and those who report they were not. Question from a monthly survey to the retail sector from Fedesarrollo.

XI. Δ Occupied: the annual change in the number of people that are working in the economy as measured by DANE.

XII. %Cred - %GDP: the difference between the annual growth of nominal outstanding credit and nominal GDP.

XIII. %M3 - %GDP: the difference between the annual growth of M3 and nominal GDP.

XIV. Money_GAP: the money gap defined as the observed money demand minus an estimated equilibrium money demand.

XV. HP: the Hodrick and Prescott filter.

XVI. BP: the Band Pass filter.

XVII. CD_GAP: the output gap that results from a Cobb-Douglas production function using NAICU and NAIRU levels for potential GDP.

XVIII. HP_*Priors*: the Hodrick and Prescott filter with *priors*[30].

XIX. NAIRU_GAP: the difference between the unemployment rate and the NAIRU estimated by Julio (2001).

XX. NAICU_GAP: the difference between the observed capacity utilization as measured by Fedesarrollo and the non inflationary level of capacity utilization (NAICU) estimated by Nigrinis (2003).

XXI. Energy_GAP: the difference between the energy demand as measured by the Electric Provider (ISA) and its long run trend (HP filter).

XXII. %GDP: annual growth of the GDP.[31]

XXIII. GAP_Kalman: the output GAP from a multivariate Kalman filter.

(Insert Table 1 here)

In Figure 2 are presented the graphs of each of the measures or *proxies* of the output gap considered for the estimation of the indicator[32]. All of them show the expansion of the economy in the first part of the past decade until 1998 and then the recession of the end of the decade. As mentioned earlier, all of them vary the magnitude of the expansion and the recession; however, the percentage difference between the highest point in the hill and the lowest point in the valley is equivalent along all measures (approximately 33%). This relation does not only hold in extreme points. As mentioned earlier, the correlation between all the series is generally above 0.8 implying that the changes in all of the series are similar even though their level varies significantly.

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[30] This was the official measure for the output gap of the Inflation Department until September 2005, when the methodology proposed in this document began to be considered. The *priors* come from the result of the production function model and are adjusted with expert judgment from the staff.

[31] The GDP growth is a good measure of the output gap if the growth of the non-inflationary GDP is constant and can be estimated by adding a constant in the regression.

[32] The graphs of the demand as the main problem for the industry, the trade balance in dollars, the external net demand and the NAIRU gap have an inverted scale in order for them to be comparable to the other measures and to the economic cycle.

B. Estimation

The twenty three measures that are considered in this exercise have different characteristics that should be exploited efficiently in order to obtain a useful output gap indicator. Some of them come from monthly and others from quarterly data, the estimation technique varies, some consider only a sector of the economy and other are aggregated. Some of them are subject to revisions and others are definite, and some are directly measured while others are estimated. Thus, by using PCA it is possible to exploit efficiently the different characteristics from each of the series in order to obtain one indicator that summarizes the information contained in each of them.

According to Peña and Poncela (2006), estimated data should not be included in the data set when using PCA because it is problematic to estimate a common component from estimations. Since these estimated measures contain errors that may be included as part of the common component if the errors have some cross-sectional correlation. Therefore, we divided the twenty measures and *proxies* into two groups. The first is the data group, which consists of variables that come from surveys or from direct measures in the economy, which includes: the lack of demand as the main problem in the industry, capacity utilization (as measured by ANDI and Fedesarrollo), trade balance in dollars, extra hours in the industry, the relation between installed capacity and expected demand, the percentage of businesses with a capacity utilization above its historical average, the external net demand, the square meters approved in construction licenses, retail sales, growth in the occupied, the difference between the growth in nominal credit and nominal GDP, GDP growth and the difference between the growth of M3 and nominal GDP. The second group contains the remaining seven measures that come from estimations based on statistical filters such as: Hodrick and Prescott filter, Hodrick and Prescott with *priors*, Band Pass filter, the Cobb-Douglas production function, the NAICU, the NAIRU, the energy gap, the money gap and the gap estimated with the Kalman filter.

In order to use PCA the series are required to be stationary, but since the variables considered in this exercise are gap measures or *proxie*s this condition is easily met as was verified with traditional unit root tests. The exercise uses quarterly data and for the monthly data the quarterly average was used. For the statistical group the gaps were constructed as the difference with the filtered series. In order to make the magnitudes comparable all the series were standarized; that is the average was subtracted and the result was then divided by the standard deviation. The resulting variable was then scaled by the standard deviation of the Hodrick and Prescott with *priors* measure, which used to be the official measure of the output gap at the Central Bank and for which the TMM is calibrated[33].

With the twenty three stationary, standardized, and scaled gaps, the first PC was calculated using all the data set (PC_All). In order to explore a possible instability in the weights of each variable in the estimated factor, an alternative estimation using rolling windows of eight years is explored. The idea is to avoid mixing in the estimation periods where the Colombian economy was different because of structural changes that have been identified by previous works[34]. More precisely the first PC is estimated for an initial sub-sample of thirty-two quarters. The next step is to replace the first observation for observation number thirty-three and the first principal component is reestimated. The process is repeated, until the last observation is included in the estimation, always with thirty-two quarters. Using this rolling windows exercise and all the series PC_All_Roll was estimated. These two procedures were repeated for the data group where PC_Data and PC_Data_Roll were estimated. In the same way using the data from the statistical estimates PC_Stat and PC_Stat_Roll were calculated. In total six additional output gap indicators were estimated, three coming from a static exercise and three using rolling windows.

In Table 2 are presented the weights for each variable in the indicator that uses all variables, in the one for the data group and for the one of the statistical group. The explained variance that is captured by the first PC is also presented for each case. Figure 3 presents the indicators estimated with all of the series in the static and in the rolling windows exercise. Figure 4 shows the same graphs for the indicators estimated with the data group and Figure 5 for the indicators that come from the group of the statistical

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[33] This scaling changes the estimated parameters in the regressions and in the estimation of the common component, but is needed in order for the output gap indicator to have a comparable level with the official measure.

[34] Among others, Misas and Melo (2004) suggest that the Colombian economy suffered from structural changes at the end of the past decade.

estimations. In order to verify the pertinence of using PCA as an aggregation methodology, we estimated three additional indicators calculated using simple averages for the three data groups mentioned above, which are shown in Figure 6.

We also decided to include into the exercise two additional *proxies* estimated with PCA. A monetary index (MI) estimated as the first principal component from the monetary measures from our data set (%Cred-%GDP and %M3-%GDP) in order to have a composite measure of monetary conditions, which should be positively correlated to the output gap. The second measure is a financial conditions index (FCI) estimated as the first principal component from a data set that includes the real credit gap, the M3 gap, real CD rate gap (3 months), the real exchange rate gap, the real gap from the average lending rate of commercial banks in all types of credit, the gap of the real federal funds rate and the gap of the real valuations of Colombia's stock index (IGBC).[35]

(Insert **Table 2** here)

(Insert Figure 3, Figure 4, Figure 5, and Figure 6 here)

C. Selection of the best measure or indicator of the output gap

Since the output gap is not directly observable, by using PCA and simple averages we only augmented the initial problem. Because we started with twenty three output gap measures and *proxie*s and we ended up with thirty four by adding the new indicators. Thus to check the validity of the indicators and of the initial measures and *proxie*s that are followed by the inflation staff we decided to verify their explanatory power of the core inflation. This is only an indirect way of gauging how good these measures are, but at least for the inflation department it is the best way of doing it. Since an adequate measure of the output gap is only important for an inflation targeting central bank if it is capable of measuring demand pressures that may push prices in the future.

The forecasts were made using a hybrid Phillips curve (4) similar to the one that is present in the TMM

[35] All the gaps were estimated as the difference of the observed values and their long run levels as estimated with the Hodrick and Prescott filter. Further information about FCI's can be found at Gauthier, et. al. (2004).

and to the one shown earlier in equation 2:

(4) $$\pi_t^c = \gamma(L)\pi_{t-1}^c + \alpha\pi_t^E + \partial_1(L) f_{1,t} + u_t ,$$

Where $\gamma(L)\pi_{t-1}^c$ includes selected lags of the non-tradable core inflation, π_t^E is the 12M expected total inflation as measured by the central bank's survey, π_t^c is the core inflation, $f_{1,t}$ is the output gap indicator, measure or *proxy* that is being tested and u_t is the error from the estimation.

We specifically test the predictive power of each of these thirty four measures as determinants of the annual non-tradable inflation excluding food and regulated prices, which accounts for about 37% of Colombian PCI and is believed to be the basket that is more closely related to the situation of the domestic demand. This is because the tradable inflation (25%) is primarily determined by the exchange rate, the food inflation (30%) is basically determined by the climate and supply shocks and the regulated prices (8%) are set by independent regulatory commissions. Furthermore, superneutrality is imposed in the Phillips Curve (e.g. the sum of the coefficients of the nominal variables $\alpha + \gamma(1)$ is restricted to one), in order to guarantee that it is vertical in the long run. A different model was estimated for each of the thirty four series that are being evaluated and the optimal lags were chosen with a stepwise methodology.

In Table 3 are presented the models chosen for each of the variables considered and the estimated coefficients. Even though, the chosen lags are different for each model the sum of the coefficients for each of the determinants (persistence, expectations and output gap) are quite similar and equivalent to the elasticities present in the TMM. For example, the average coefficient for the persistence is 0.69, for the output gap is 0.29 and for the expectations is 0.31. Only for the trade balance the estimated coefficients have the wrong sign, which casts doubt on the validity of this *proxy* which is later confirmed with the forecast evaluation.

As usual the out of sample forecasts were evaluated for various horizons using traditional goodness of fit measures. In Table 4 are presented the results of the evaluations organized by the root mean square percentage error (RMSPE). It is worth noting that some of the models present a U-Theil greater than one for most of the horizons, implying that its informational content is negligible since the forecasts errors would be smaller by assuming that the non-tradable core inflation follows a random walk[36]. This problem is especially relevant for the pure statistical measures. There are also significant differences in the quality of the forecasts, signaling that even though the correlation for the majority of the measures is usually high their informational content is not the same. For example for forecasts four quarters ahead, the mean absolute error (MAE) is 1.39 for PC_ data and almost double for the HP gap (2.62). We also tried to perform forecasts without including an output gap indicator, in order to have a stricter benchmark than the U-Theil. However, as expected the results were not satisfactory since including the GDP growth produces much better forecasts than this no-indicator benchmark and including most of the gap indicators produces better forecasts than the GDP growth.

In Table 5 is presented a ranking that summarizes the results of the forecast evaluation for each horizon. In this table PC_Data consistently appears as the best output gap measure, according to its forecasting power of the core inflation in Colombia using a hybrid Phillips Curve. Other indicators that seem to have a high informational content are Cap vs. Dd, CU_Fede, CU_ANDI and the Hodrick Prescott filter with *priors*. These results suggest that the core inflation is definitely not a random walk especially for longer horizons and is highly correlated with the capacity utilization in the industry, despite the fact that the industry only weighs 15% of Colombian GDP. The quality of HP *priors* which used to be the official measure of the Central Bank and is widely used in other countries is also verified. The ability of monetary measures to anticipate demand pressures is not very good, which is not surprising bearing in mind the instability of the money demand in Colombia in the past years. Finally de FCI seems a reasonable indicator for the very short run, but its informative power rapidly decays as should be expected.

The results also validate the ideas of Peña and Poncela (2006), who argue that the estimation of the common component is deteriorated by including in the data set variables that are estimated with

[36] For a random walk the best forecast for any horizon is the last observed value, thus no model is needed for making forecasts. In this exercise a U-Theil greater than one, implies that a purely non-stationary autoregressive model would probably produce better forecasts. Hendry and Mizon (2005) present some issues on this kind of results.

statistical procedures. The rolling window exercise was not effective as we supposed it would be and in general the estimations that used all the available information were superior. The forecasts from the indicators estimated using simple averages tend to be worse than those calculated using PCA, as was expected since in the simple averages do not filter measurement errors or extreme observations, thus verifying the relevance of the factor model. Finally it is worth noting the poor results of the pure statistical filters and the high informational content of the Colombian surveys, which is good news for the analysts since they are published with a minimum lag and are not revised.

V. Conclusions

This work explored the usefulness of PCA to efficiently summarize in one series the information contained in various measures of the output gap. The results suggest that this methodology adequately incorporates the fundamentals from each of the measures and separates the measurement errors from each of them. It also permits the aggregation of data in different formats and from diverse sources. While solving the problems involved with discretionality in the process of aggregation of the information, since the weights for each variable come from the data and are updated continuously.

The indicators were estimated from twenty three quarterly measures and *proxies* that the inflation department monitors regularly from 1990 to 2006. Using PCA six possible indicators were estimated, by dividing the information into three groups (all, data and estimations) and by making to types of estimations for each group (all the sample and rolling windows of thirty-two quarters). Three additional indicators were calculated for each group using simple averages. A MI and a FCI were also estimated using PCA. In order to verify the validity of each of the original measures and of the proposed indicators, out of sample forecasts using the best hybrid Phillips Curve for each measure were evaluated. Using standard criterions for forecast evaluation, the PC estimated from observed data and using the whole sample (PC_Data) turned out to be the most adequate to signal demand pressures that may push prices in the future.

The results are encouraging for the estimation of the level of the output gap in real time, since most of the data needed for this indicator is not subject to revisions and is published with minimum lag. The indicator is quite useful for the inflation department as it provides a reliable estimate that uses efficiently all the available information and thus facilitates better policy recommendations to the Board of Governors in an inflation targeting country such as Colombia. Further work is still required in order to asses the importance of working with dynamic estimators for the Colombian case, nonetheless up to now no one has found empirically their alleged theoretical advantage.

VI. References

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Figure 1
Output Gap According to Various Measurements

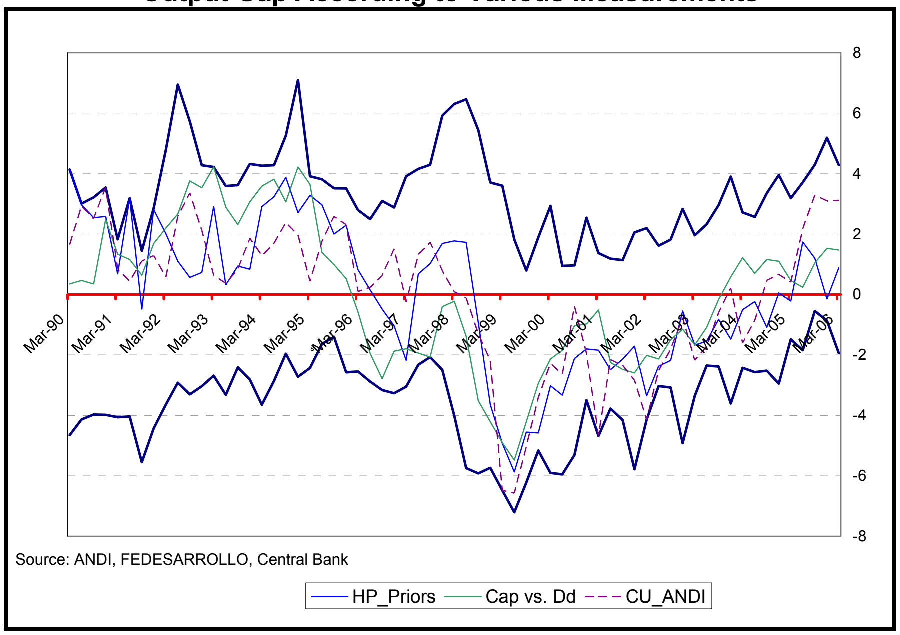
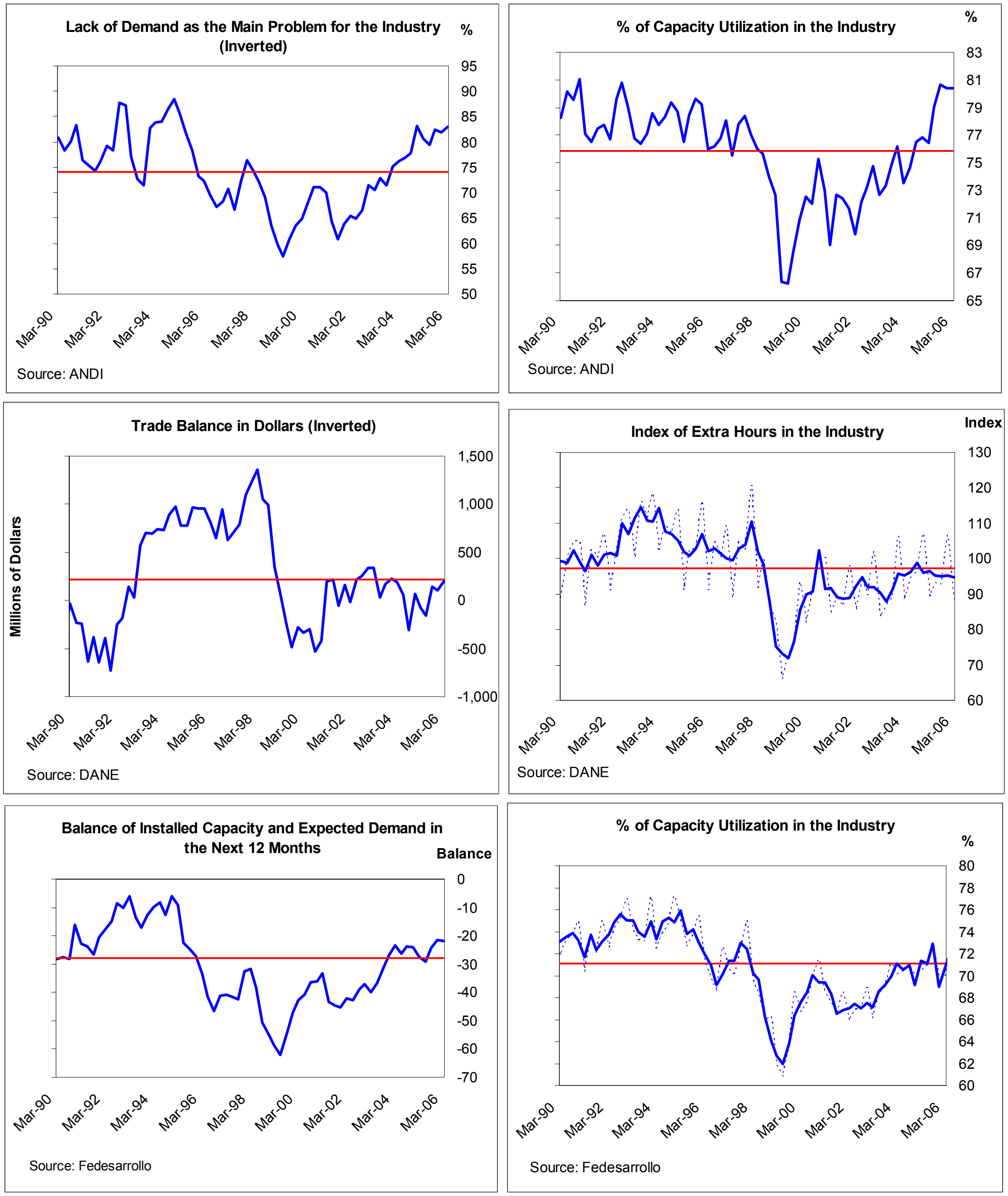
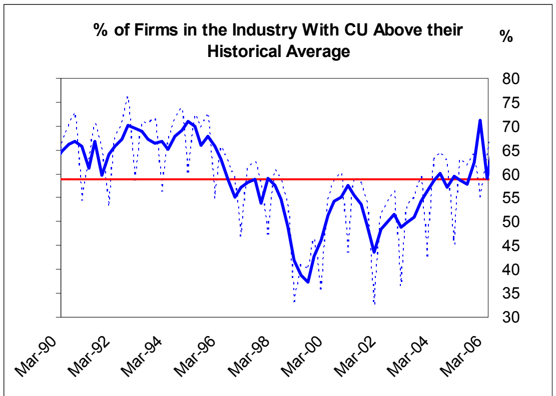


Table 1
Acronyms for the measures that were used for the estimation

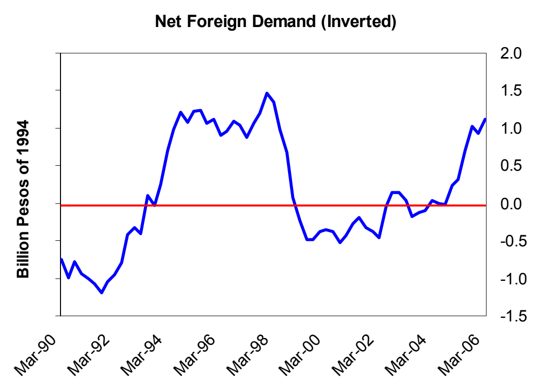
	Acronym	Indicator	Source
1	Dd_ANDI	% of entrepreneurs who think the main problem for business is the lack of demand	ANDI
2	CU_ANDI	% capacity utilization in the industry	ANDI
3	Tr_B	Trade balance in dollars	DANE
4	Extra_H	Index of extra hours worked in the industry	DANE
5	Cap vs. Dd	Balance of entrepreneurs who think their installed capacity is enough to serve their expected demand	Fedesarrollo
6	CU_FEDE	% capacity utilization in the industry	Fedesarrollo
7	% CU > Av	% of business with capacity utilization is above its historical average	Fedesarrollo
8	Net_Ext_Dd	The net external demand in pesos of 1994 as measured in the national accounts	DANE
9	Lics	Square meters approved in construction licenses	DANE
10	Ret_Sal	Balance, retail sales from the past month were better than the same month a year ago	Fedesarrollo
11	Δ Occupied	Annual growth in the number of people who are working in the economy	DANE
12	%Cred - %GDP	Difference between the annual growth of nominal outstanding credit and nominal GDP	Authors Estimations
13	%M3 - %GDP	Difference between the annual growth of M3 and nominal GDP	Authors Estimations
14	HP	The Hodrick and Prescott filter	Authors Estimations
15	BP	The Band Pass filter	Authors Estimations
16	CD_GAP	Output gap that results from a Cobb-Douglas production function	Authors Estimations
17	HP_*Priors*	Hodrick and Prescott filter with *priors*	CB Estimations
18	NAIRU_GAP	Difference between the unemployment rate and the NAIRU	CB Estimations
19	NAICU_GAP	Difference between CU as measured by Fedesarrollo and the NAIRU	CB Estimations
20	Energy_GAP	Difference between the energy demandand and its long run trend	CB Estimations
21	%GDP	Annual growth of the GDP	DANE
22	GAP_Kalman	The output GAP from a multivariate Kalman filter	CB Estimations
23	Money gap	Observed money demand minus an estimated equilibrium money demand	CB Estimations
24	Monetary Index	A monetary index estimated as the first principal component from series 12 and 13	Authors Estimations
25	FCI	A Financial Conditions Index estimated as the first prncipal component from various financial series	Authors Estimations
26	Average all	Average of all indicators	Authors Estimations
27	Average data	Average of data indicators	Authors Estimations
28	Average Stat	Average of statisticaly estimated indicators	Authors Estimations
29	PC_ALL	Principal Component estimated with all the series using all the available data	Authors Estimations
30	PC_ALL_ROLL	Principal Component estimated with all the series using rolling windows of 32 quarters	Authors Estimations
31	PC_DATA	Principal Component estimated with the series from the data group using all the available data	Authors Estimations
32	PC_DATA_ROLL	Principal Component estimated with the series from the data group using rolling windows of 32 quarters	Authors Estimations
33	PC_STAT	Principal Component estimated with the series from the statistical estimates using all the available data	Authors Estimations
34	PC_STAT_ROLL	Principal Component estimated with the series from the statistical estimates using using rolling windows of 32 quarters	Authors Estimations

Figure 2
Different measures and *proxies* for the output gap in Colombia

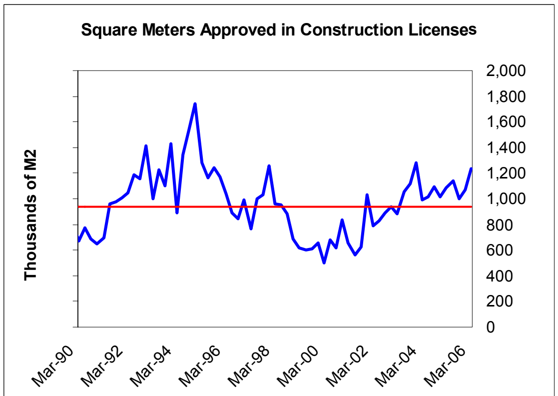




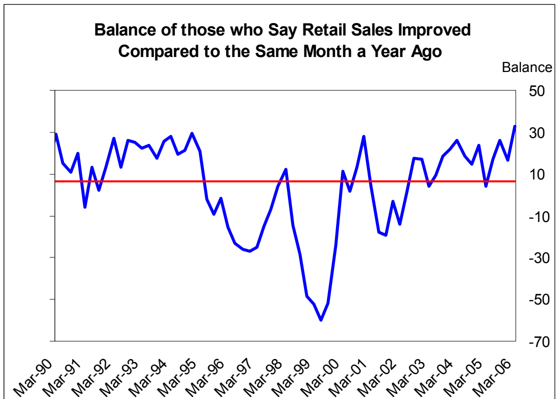
Source Fedesarrollo



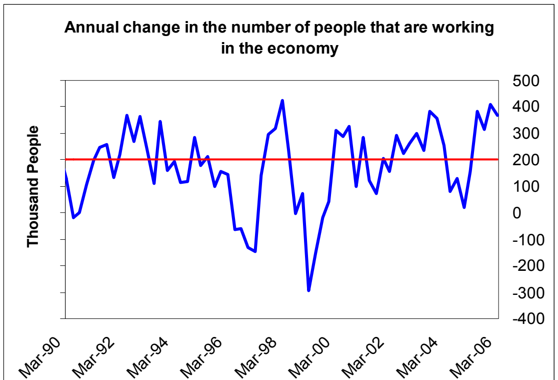
Source: DANE



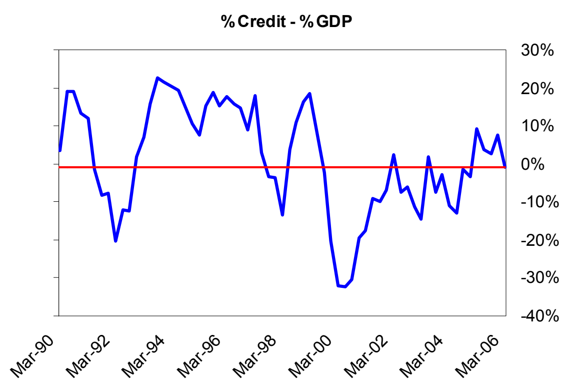
Source: DANE



Source: Fedesarrollo

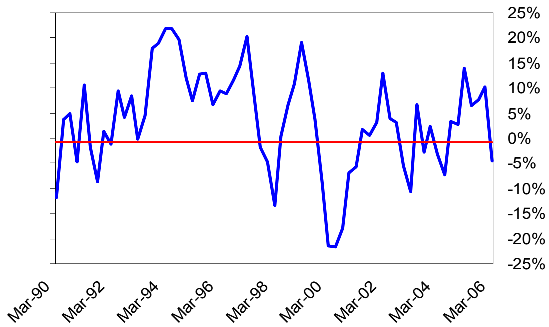


Source: DANE



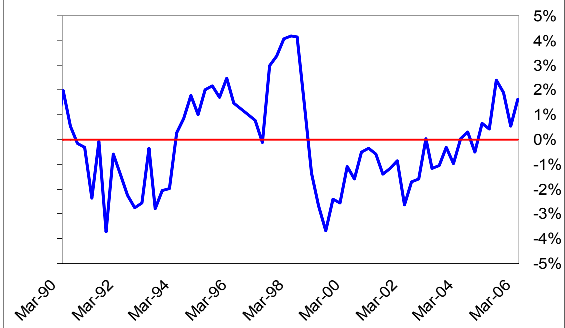
Source: Central Bank Estimation

% M3 - % GDP



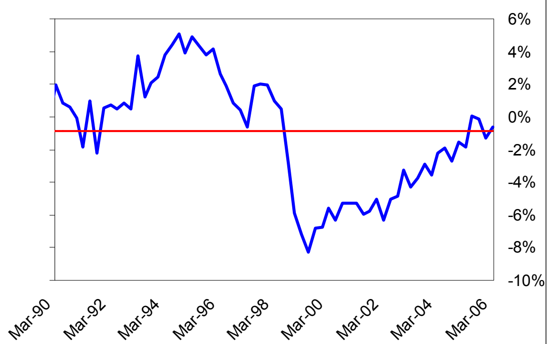
Source: Central Bank Estimation

Hodrick and Prescott Filter



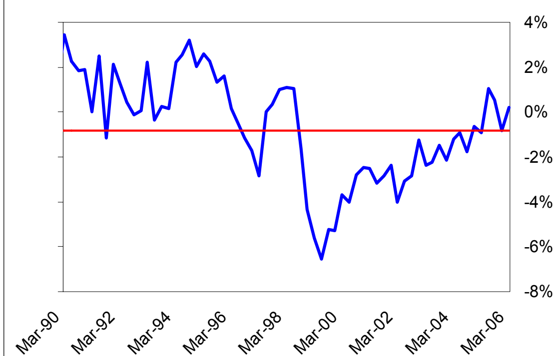
Source: Authors Estimations

Gap Estimated with a Cobb-Douglas Production Function



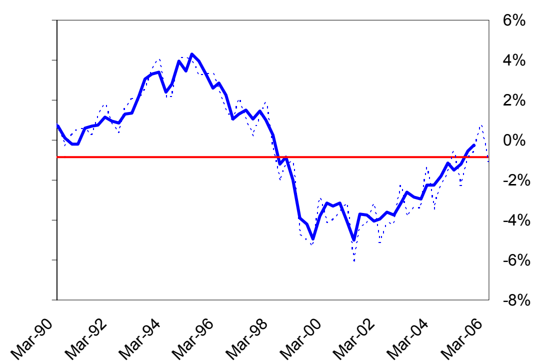
Source: Central Bank Estimation

Hodrick and Prescott with Priors



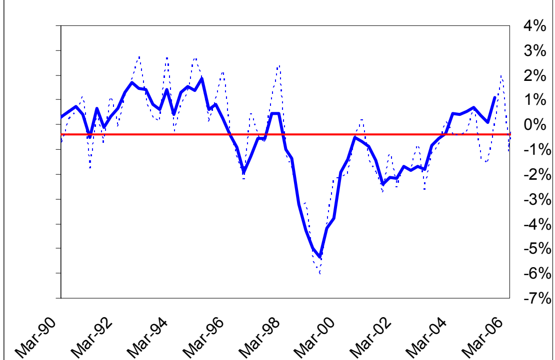
Source: Central Bank Estimation

Gap Estimated with the NAIRU



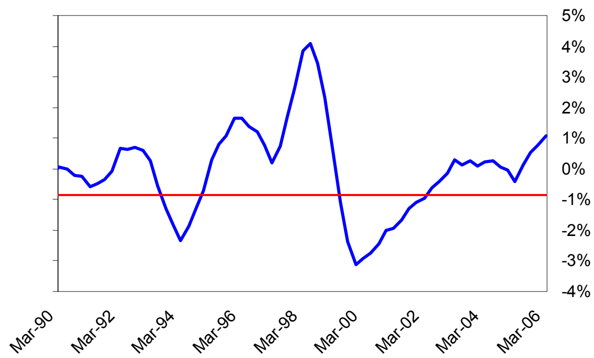
Source: Central Bank Estimation

Gap Estimated with the NAICU



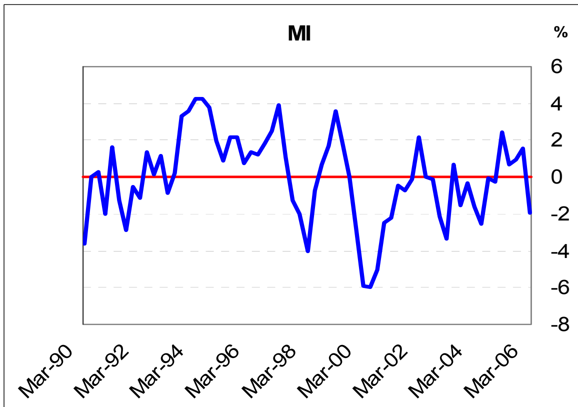
Source: Central Bank Estimation

Gap of Energy Demand



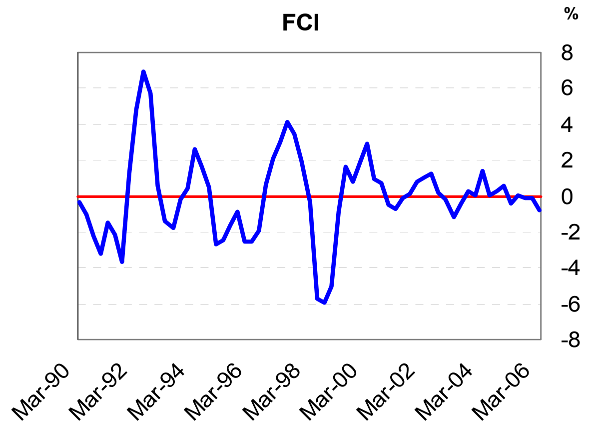
Source: Central Bank Estimation

MI



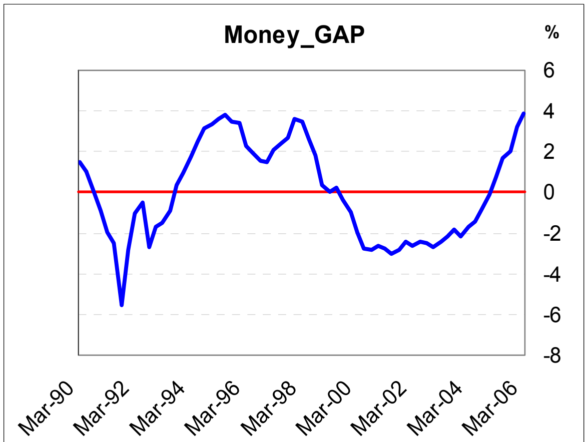
Source: Author's Estimations

FCI



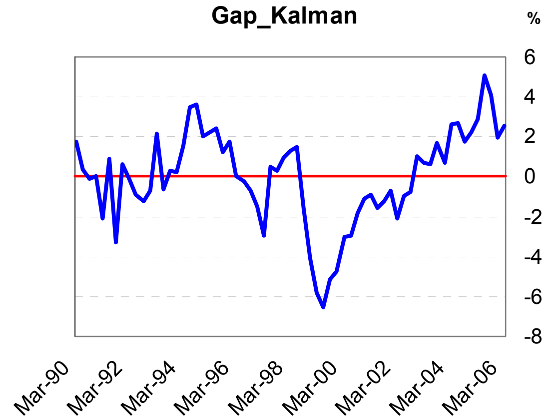
Source: Author's Estimations

Money_GAP



Source: Central Bank Estimations

Gap_Kalman



Source: Central Bank Estimations

Table 2

Weights for each measure in the first estimated static PC for each group

Proxy or Measure	ALL	DATA	STATISTICS
	GROUP		
Gap Kalman	6%		12%
Dd_ANDI	6%	12%	
CU ANDI	7%	11%	
Tr_B	2%	2%	
Extra_H	5%	8%	
Cap vs. Dd	6%	12%	
Licenses	5%	9%	
Ret_Sal	4%	9%	
CU Fede	7%	12%	
Net_Ext_Dd	2%	2%	
% CU > Av	3%	6%	
HP	3%		12%
BP	3%		8%
NAIRU_GAP	6%		12%
NAICU_GAP	7%		10%
CD_GAP	8%		16%
HP_Priors	7%		15%
Δ Occupied	1%	3%	
Energy_GAP	1%		5%
%Cred - %GDP	1%	1%	
%M3 - %GDP	1%	1%	
Money Gap	3%		9%
%GDP	7%	12%	
Explained Variance	49%	49%	58%

Figure 3

First PC for all the series in the static and rolling exercise

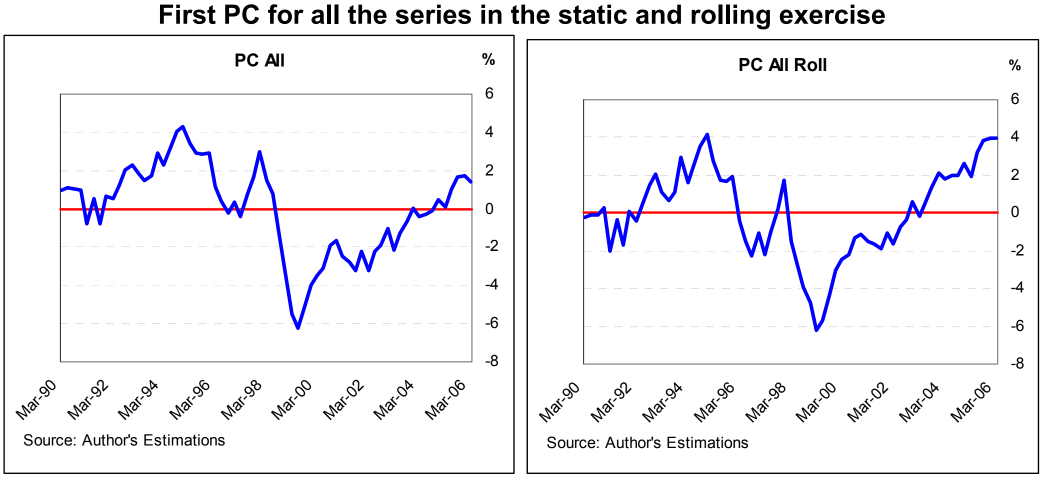
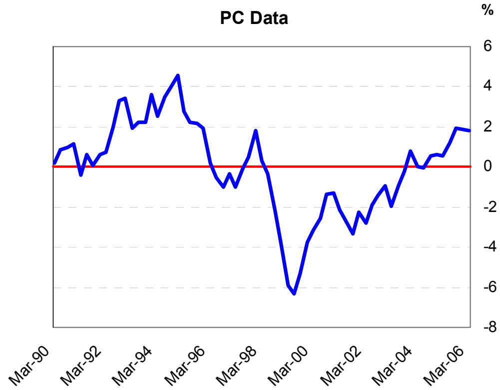
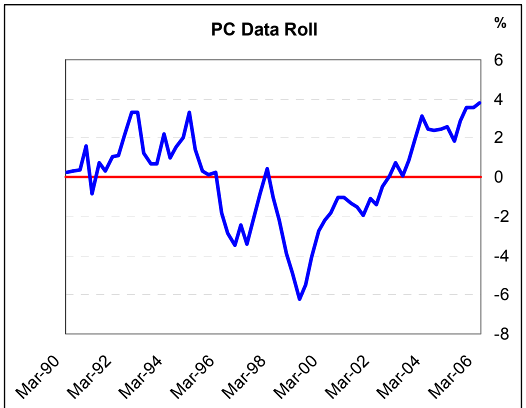


Figure 4
First PC for the group of data in the static and rolling exercise

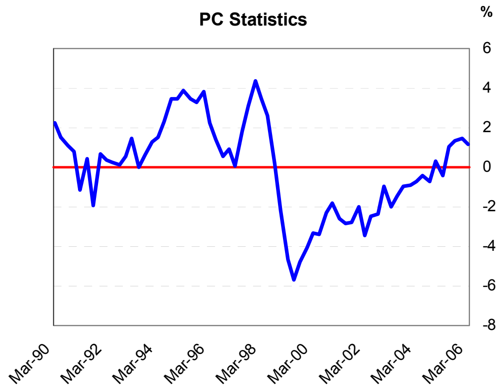


Source: Author's Estimations

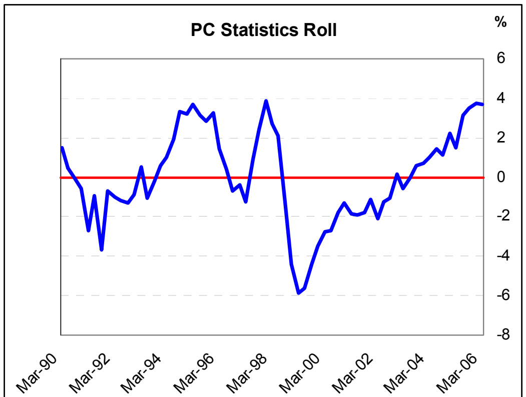


Source: Author's Estimations

Figure 5
First PC for the group of filters in the static and rolling exercise



Source: Author's Estimations



Source: Author's Estimations

Figure 6
Indicators estimated using simple averages for the three data groups

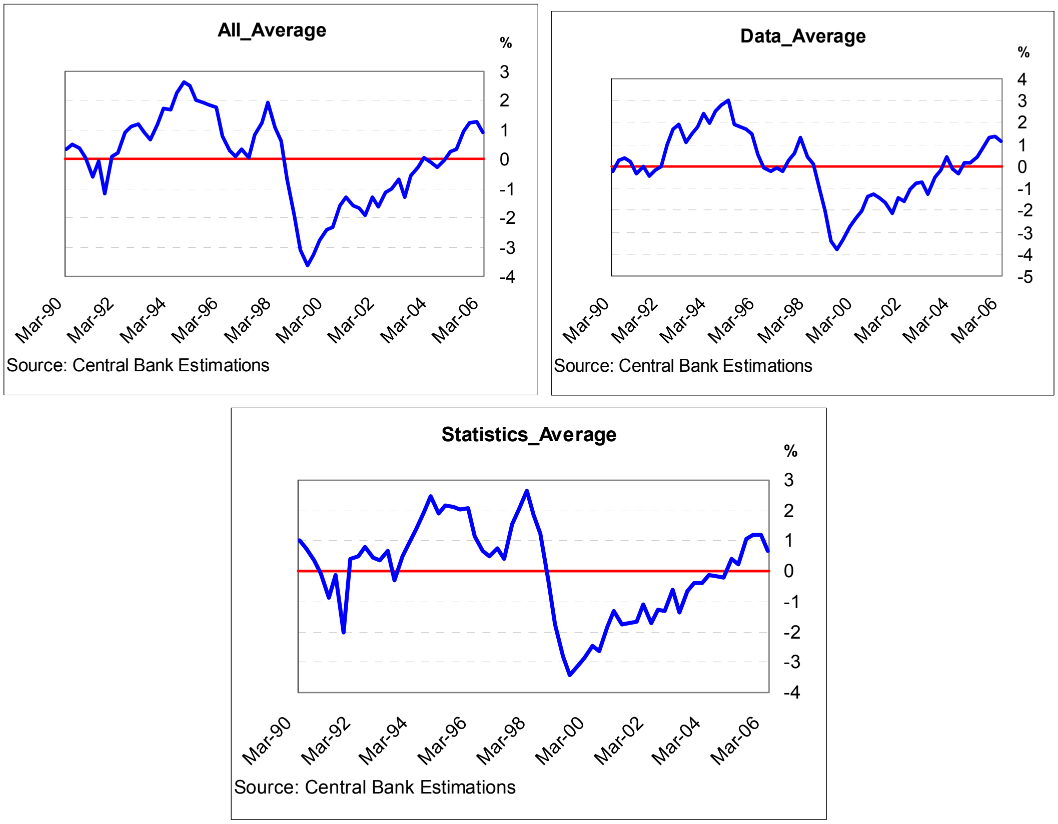


Table 3

Selected Hybrid Phillips Curves for each of the output gap measures

1	Dd_ANDI	Beta	p_val
	Y1	0.61	0.00
	X1	0.22	0.12
	X4	0.33	0.05
	EXPECT	0.38	0.00

2	CU_ANDI	Beta	p_val
	Y1	0.54	0.00
	Y2	0.22	0.07
	X2	0.34	0.01
	EXPECT	0.22	0.02

3	Tr_B	Beta	p_val
	Y1	0.56	0.00
	Y2	0.30	0.03
	X1	0.30	0.08
	X5	-0.37	0.01
	EXPECT	0.11	0.32

4	Extra_H	Beta	p_val
	Y1	0.60	0.00
	X1	0.58	0.00
	X5	-0.27	0.10
	X6	0.43	0.00
	EXPECT	0.38	0.00

5	Cap vs. Dd	Beta	p_val
	Y1	0.45	0.00
	X1	0.49	0.01
	X3	-0.58	0.11
	X4	0.48	0.18
	X6	0.46	0.04
	EXPECT	0.53	0.00

6	CU_FEDE	Beta	p_val
	Y1	0.52	0.00
	X1	0.47	0.00
	X6	0.32	0.03
	EXPECT	0.45	0.00

7	% CU > Av	Beta	p_val
	Y1	0.55	0.00
	X1	0.24	0.07
	X3	0.27	0.05
	X4	0.24	0.08
	EXPECT	0.43	0.00

8	Net_Ext_Dd	Beta	p_val
	Y1	0.78	0.00
	X1	0.54	0.02
	X4	-1.34	0.02
	X5	1.65	0.03
	X6	-0.88	0.05
	EXPECT	0.19	0.06

9	Lics	Beta	p_val
	Y1	0.53	0.00
	Y4	-0.15	0.15
	X1	0.49	0.00
	X6	0.53	0.00
	EXPECT	0.62	0.00

10	Ret_Sal	Beta	p_val
	Y1	0.53	0.00
	Y2	0.27	0.03
	X2	0.35	0.02
	X4	-0.40	0.09
	X5	0.47	0.02
	EXPECT	0.18	0.08

11	% Occupied	Beta	p_val
	Y1	0.61	0.00
	Y2	0.34	0.01
	X1	0.45	0.00
	X3	-0.32	0.03
	X5	0.65	0.00
	X6	-0.33	0.03
	EXPECT	0.02	0.81

12	%Cred - %GDP	Beta	p_val
	Y1	0.65	0.00
	Y2	0.28	0.04
	X5	-0.16	0.22
	EXPECT	0.05	0.61

13	%M3 - %GDP	Beta	p_val
	Y1	0.63	0.00
	Y2	0.26	0.07
	Y4	-0.16	0.17
	X3	0.25	0.09
	EXPECT	0.27	0.02

14	HP	Beta	p_val
	Y1	0.61	0.00
	Y2	0.31	0.03
	X2	0.27	0.14
	X3	-0.32	0.10
	X6	-0.23	0.08
	EXPECT	0.05	0.60

15	BP	Beta	p_val
	Y1	0.55	0.00
	Y2	0.30	0.05
	Y3	0.27	0.08
	Y4	-0.17	0.22
	X1	-6.06	0.03
	X2	21.30	0.02
	X3	-30.56	0.02
	X4	21.20	0.02
	X5	-6.24	0.02
	EXPECT	0.02	0.87

16	CD GAP	Beta	p_val
	Y1	0.55	0.00
	X2	0.87	0.00
	X4	-0.35	0.16
	EXPECT	0.43	0.00

17	HP_Priors	Beta	p_val
	Y1	0.57	0.00
	Y2	0.21	0.10
	X2	0.56	0.01
	X3	-0.27	0.21
	EXPECT	0.20	0.04

18	NAIRU_GAP	Beta	p_val
	Y1	0.53	0.00
	X1	0.58	0.00
	EXPECT	0.44	0.00

19	NAICU_GAP	Beta	p_val
	Y1	0.45	0.00
	Y2	0.25	0.03
	X1	0.28	0.06
	X2	0.26	0.10
	EXPECT	0.27	0.00

20	Energy_GAP	Beta	p_val
	Y1	0.62	0.00
	Y2	0.31	0.03
	X2	0.93	0.06
	X3	-1.80	0.02
	X5	1.87	0.01
	X6	-1.24	0.02
	EXPECT	0.05	0.64

21	PC All	Beta	p_val
	Y1	0.62	0.00
	X1	0.48	0.00
	EXPECT	0.36	0.00

22	PC Stat	Beta	p_val
	Y1	0.59	0.00
	Y2	0.22	0.09
	X2	0.64	0.02
	X3	-0.49	0.07
	EXPECT	0.17	0.11

23	PC Data	Beta	p_val
	Y1	0.45	0.00
	X1	0.48	0.00
	X6	0.37	0.02
	EXPECT	0.53	0.00

24	PC All Roll	Beta	p_val
	Y1	0.47	0.00
	Y2	0.26	0.03
	X2	0.44	0.00
	EXPECT	0.27	0.01

25	PC Stat Roll	Beta	p_val
	Y1	0.59	0.00
	Y2	0.24	0.06
	X2	0.54	0.02
	X3	-0.42	0.09
	EXPECT	0.15	0.13

26	PC Data Roll	Beta	p_val
	Y1	0.50	0.00
	Y2	0.29	0.03
	X2	0.66	0.02
	X3	-0.51	0.12
	X5	0.27	0.21
	EXPECT	0.19	0.11

27	MI	Beta	p_val
	Y1	0.63	0.00
	Y2	0.26	0.07
	Y4	-0.16	0.17
	X3	0.25	0.09
	EXPECT	0.27	0.02

28	FCI	Beta	p_val
	Y1	0.61	0.00
	Y2	0.28	0.03
	X1	-0.22	0.12
	X3	0.61	0.00
	X4	-0.39	0.05
	EXPECT	0.09	0.31

29	GDP growth	Beta	p_val
	C	-1.61	0.02
	Y1	0.53	0.00
	Y2	0.21	0.09
	X2	0.50	0.00
	X3	-0.28	0.06
	EXPECT	0.30	0.01

30	Average All	Beta	p_val
	Y1	0.62	0.00
	X1	0.65	0.00
	EXPECT	0.38	0.00

31	Average Data	Beta	p_val
	Y1	0.57	0.00
	X1	0.81	0.00
	EXPECT	0.43	0.00

32	Average Statistics	Beta	p_val
	Y1	0.60	0.00
	Y2	0.21	0.11
	X2	0.82	0.02
	X3	-0.69	0.05
	EXPECT	0.19	0.08

33	Gap Kalman	Beta	p_val
	Y1	0.61	0.00
	Y2	0.20	0.12
	X2	0.51	0.01
	X3	-0.31	0.12
	EXPECT	0.19	0.06

34	Money Gap	Beta	p_val
	Y1	0.52634	0.00
	Y3	0.14724	0.28
	X2	0.46034	0.01
	X6	-0.02206	0.90
	EXPECT	1	1.92

35	No Indicator	Beta	p_val
	Y1	0.63	0.00
	Y2	0.22	0.09
	EXPECT	0.15	0.09

Table 4
Forecast evaluation for each measure for various horizons (Mar-98 Mar-06)

H=1 N=33	ME	MAE	MAPE	RMSE	RMSPE	UTHEIL
Δ Occupied	-0.79	1.2	23.22	1.79	36.2	0.98
PC Data	-0.16	1.19	24.9	1.6	39.47	0.87
Licenses	-0.34	1.47	31.55	1.81	41.61	0.99
Cap vs. Dd	-0.32	1.14	25.99	1.53	43.51	0.84
%M3 - %GDP	-0.69	1.28	29.3	1.8	43.84	0.98
Ret_Sal	-0.56	1.3	28.81	1.73	44.28	0.95
Dd ANDI	-0.38	1.28	28.34	1.72	47.9	0.94
Average All	-0.58	1.31	27.8	1.75	49.16	0.96
FCI	-0.87	1.37	29.48	1.85	49.37	1.01
Average Data	-0.52	1.27	27.99	1.67	49.38	0.92
NAIRU_GAP	-0.27	1.29	27.99	1.79	49.74	0.98
CD_GAP	-0.46	1.33	27.64	1.9	50.22	1.04
Extra_H	-0.46	1.29	28.4	1.73	50.61	0.95
Money Gap	-1.06	1.5	34.42	1.83	50.68	1.00
PC Data ROLL	-0.44	1.43	32.52	1.78	50.87	0.97
PC All	-0.5	1.28	27.6	1.76	51.26	0.96
PC Stat ROLL	-0.86	1.36	29.65	1.88	52.04	1.03
CU Fede	-0.15	1.12	25.91	1.62	52.86	0.89
%GDP	-0.48	1.38	29.74	1.88	53.25	1.03
HP_Priors	-0.55	1.27	28.32	1.78	53.53	0.98
Gap Kalman	-0.84	1.41	31.74	1.85	54.44	1.01
PC All ROLL	-0.7	1.41	33.03	1.78	54.69	0.98
CU ANDI	-0.3	1.36	30.39	1.82	55.35	0.99
% CU > Av	-0.32	1.32	30.29	1.82	55.42	0.99
No Indicator	-0.8	1.26	29.79	1.82	55.47	1.00
Tr_B	-0.85	1.55	33.41	2	56.59	1.09
MI	-0.73	1.4	33.15	1.96	60.04	1.07
NAICU_GAP	-0.4	1.25	29.08	1.75	61.32	0.96
PC Stat	-0.85	1.39	31.64	1.93	61.47	1.06
Energy_GAP	-0.72	1.35	33.51	1.76	61.62	0.96
Average Stat	-0.89	1.4	32.1	1.95	62.47	1.07
%Cred - %GDP	-0.91	1.34	32.71	1.9	64.61	1.04
Net_Ext_Dd	-0.95	1.54	37.41	1.98	66.65	1.09
HP	-0.83	1.39	34.47	1.88	68.82	1.03
BP	-1.38	1.77	40.36	2.75	84.72	1.46

H=4 N=30	ME	MAE	MAPE	RMSE	RMSPE	UTHEIL
PC Data	-0.11	1.39	28.77	1.88	37.24	0.56
Cap vs. Dd	-0.57	1.3	29.27	1.81	41.03	0.53
Licenses	-0.47	2.3	48.62	2.59	53.94	0.77
CU Fede	-0.24	1.15	28.02	1.78	56.71	0.53
NAIRU_GAP	-0.24	1.44	33.92	2.05	57.34	0.60
Average All	-0.86	1.32	31.45	2.01	57.38	0.59
Average Data	-0.72	1.34	32.65	1.91	58.28	0.56
Ret_Sal	-1.43	2.1	46.72	2.6	59.16	0.77
Dd ANDI	-0.75	1.82	40.91	2.46	60.43	0.73
PC All	-0.67	1.26	31.18	1.98	61.36	0.58
PC Data ROLL	-0.96	2.26	50.68	2.73	62.96	0.81
% CU > Av	-0.61	1.62	36.85	2.4	65.78	0.71
CD_GAP	-0.62	1.38	34.19	2.14	66.51	0.63
CU ANDI	-0.32	1.74	39.47	2.53	67.23	0.75
Δ Occupied	-2.44	2.53	53.58	3.48	69.27	1.03
PC All ROLL	-1.23	1.88	45.91	2.47	73.22	0.73
Extra_H	-0.96	1.51	37.91	2.21	73.72	0.65
HP_Priors	-1.23	1.62	38.56	2.63	75.63	0.78
NAICU_GAP	-0.55	1.23	32.82	1.97	76.59	0.58
PC Stat ROLL	-1.98	2.05	47.81	3.11	79.29	0.92
%M3 - %GDP	-1.8	2.41	55.03	3.32	79.5	0.98
Gap Kalman	-1.93	2.19	52.02	2.9	81.97	0.86
Money Gap	-2.67	2.82	67.72	3.25	86.79	0.96
%GDP	-0.68	1.73	43.41	2.63	88.17	0.78
Tr_B	-1.81	2.34	56.66	3.11	92.47	0.92
MI	-2.33	2.56	59.39	3.83	92.63	1.13
Net_Ext_Dd	-2.37	2.55	65	2.97	95.47	0.88
No Indicator	-2.19	2.29	56.11	3.35	96.38	0.99
FCI	-2.25	2.55	59.69	3.63	98.96	1.07
PC Stat	-2.09	2.19	54.75	3.32	105.75	0.98
%Cred - %GDP	-2.88	2.94	71.01	3.98	107.13	1.17
Energy_GAP	-2.5	2.9	73.15	3.77	110.61	1.11
Average Stat	-2.27	2.35	58.9	3.5	111.96	1.03
HP	-2.3	2.62	70.16	3.4	132.7	1.00
BP	-4.84	5.25	125.03	7.54	222.15	2.15

H=6 N=28	ME	MAE	MAPE	RMSE	RMSPE	UTHEIL
PC Data	0.18	1.14	26.07	1.42	32.28	0.37
Cap vs. Dd	-0.35	1.18	27.83	1.58	37.96	0.42
CU ANDI	0.1	1.28	30.71	1.68	46.36	0.44
Average All	-0.51	0.91	26.32	1.17	47.83	0.31
Licenses	-0.19	1.96	43.98	2.25	50.14	0.59
Dd ANDI	-0.46	1.53	37.19	1.93	50.42	0.51
CU Fede	-0.04	0.92	25.8	1.21	50.49	0.32
Average Data	-0.44	1.05	28.8	1.35	51.26	0.36
Ret_Sal	-1.49	1.95	43.04	2.35	52.2	0.62
PC All	-0.32	0.88	25.99	1.21	52.82	0.32
% CU > Av	-0.33	1.28	32.36	1.64	53.07	0.43
NAIRU_GAP	0.15	1.13	30.67	1.43	53.68	0.38
CD_GAP	-0.3	0.94	27.61	1.27	56.8	0.33
HP_Priors	-1.01	1.26	34.59	1.76	62.95	0.47
PC Data ROLL	-0.89	2.32	51.23	2.84	63.59	0.75
PC All ROLL	-1.23	1.94	48.16	2.41	66.19	0.64
Gap Kalman	-1.83	2.07	51.44	2.35	67.01	0.62
NAICU_GAP	-0.41	0.99	29.93	1.43	67.98	0.38
Extra_H	-0.76	1.21	35.63	1.67	71.77	0.44
%GDP	-0.41	1.38	38.08	1.83	72.1	0.48
Δ Occupied	-2.77	2.77	63.18	3.32	73.34	0.88
PC Stat ROLL	-1.91	1.91	49.73	2.42	73.93	0.64
%M3 - %GDP	-1.76	2.29	55	3.27	81.3	0.86
Tr_B	-1.82	2.04	56.6	2.65	88.08	0.70
Money Gap	-3.25	3.25	81.05	3.51	94.98	0.93
Net_Ext_Dd	-2.47	2.52	68.13	2.84	96.24	0.75
MI	-2.6	2.74	66.55	4	99.18	1.06
No Indicator	-2.55	2.57	66.81	3.56	107.49	0.94
PC Stat	-2.12	2.21	61.65	2.86	111.21	0.75
FCI	-2.45	2.57	67.34	3.52	112.27	0.93
Average Stat	-2.38	2.46	67.97	3.14	120.54	0.83
Energy_GAP	-3.36	3.46	88.52	4.54	122.38	1.20
%Cred - %GDP	-3.77	3.77	93.84	4.65	123.2	1.23
HP	-2.76	2.91	81.15	3.53	136.84	0.93
BP	-5.54	6.06	153.47	8.13	242.03	2.07

H=8 N=26	ME	MAE	MAPE	RMSE	RMSPE	UTHEIL
Cap vs. Dd	-0.09	0.97	24.07	1.32	32.99	0.34
PC Data	0.32	1.15	28.08	1.44	36.32	0.37
CU ANDI	0.44	1.15	29.04	1.4	40.79	0.36
Average All	-0.42	0.93	26.41	1.2	45.8	0.31
Dd ANDI	-0.2	1.36	35.17	1.65	47.75	0.42
Average Data	-0.46	1.09	29.77	1.37	48.13	0.35
PC All	-0.28	0.93	26.74	1.26	49.07	0.32
Licenses	-0.09	1.93	44.06	2.26	50.86	0.58
Ret_Sal	-1.24	1.91	44.29	2.18	51.04	0.56
% CU > Av	-0.02	1.11	30.63	1.32	51.62	0.34
NAIRU_GAP	0.32	1.06	30.04	1.37	54.37	0.35
%GDP	-0.56	1.33	35.24	1.76	56.95	0.45
CD_GAP	-0.33	1.02	30.33	1.36	60.07	0.35
PC All ROLL	-1.38	2.06	49.74	2.56	63.89	0.65
HP_Priors	-0.8	1.08	33.02	1.42	65.17	0.36
PC Data ROLL	-0.8	2.44	54.77	2.97	67.12	0.76
NAICU_GAP	-0.46	1.07	32.14	1.53	67.66	0.39
CU Fede	0.04	0.87	28.35	1.28	68.17	0.33
Gap Kalman	-1.73	2.04	51.9	2.44	69.59	0.62
Δ Occupied	-2.79	2.79	67.01	3.01	73.52	0.77
%M3 - %GDP	-1.4	2.12	52.24	3.06	77.83	0.78
PC Stat ROLL	-1.78	1.78	50.61	2.15	78.9	0.55
Extra_H	-0.52	0.97	33.3	1.53	83.8	0.39
MI	-2.32	2.43	62.1	3.41	88.91	0.87
Tr_B	-2	2.54	67.72	3.08	92.26	0.79
Net_Ext_Dd	-2.56	2.66	72.18	2.97	98.01	0.76
Money Gap	-3.76	3.76	95.29	3.94	107.69	1.01
PC Stat	-2.02	2.12	63.37	2.8	117.89	0.71
No Indicator	-2.66	2.7	74.67	3.57	120.19	0.91
FCI	-2.55	2.6	72.35	3.51	120.89	0.90
Average Stat	-2.33	2.41	71.16	3.12	128.37	0.80
Energy_GAP	-3.95	4.05	105.52	5.22	142.62	1.33
HP	-3.29	3.55	97.65	4.04	148.01	1.03
%Cred - %GDP	-4.39	4.39	115.06	5.06	148.62	1.29
BP	-5.44	6.04	164.29	7.8	257.75	1.91

Table 5
Summary of the best output gap measures for various horizons

Ranking	1 Qtr.	2 Qtr.	3 Qtr.	4 Qtr.	5 Qtr.	6 Qtr.	7 Qtr.	8 Qtr.	Ranking
1	Δ Occupied	**PC Data**	**PC Data**	**PC Data**	**PC Data**	**PC Data**	**PC Data**	Cap vs. Dd	1
2	**PC Data**	Ret_Sal	Cap vs. Dd	Cap vs. Dd	Cap vs. Dd	Cap vs. Dd	Cap vs. Dd	**PC Data**	2
3	Licenses	Cap vs. Dd	Ret_Sal	Licenses	Average All	CU ANDI	CU ANDI	CU ANDI	3
4	Cap vs. Dd	Δ Occupied	CU Fede	CU Fede	CU Fede	Average All	Licenses	Average All	4
5	%M3 - %GDP	Licenses	Average All	NAIRU_GAP	Licenses	Licenses	Average All	Dd ANDI	5
6	Ret_Sal	%M3 - %GDP	Licenses	Average All	Ret_Sal	Dd ANDI	CU Fede	Average Data	6
7	Dd ANDI	NAIRU_GAP	Dd ANDI	Average Data	Average Data	CU Fede	Dd ANDI	PC All	7
8	Average All	Average All	NAIRU_GAP	Ret_Sal	Dd ANDI	Average Data	Average Data	Licenses	8
9	FCI	PC Data ROLL	PC Data ROLL	Dd ANDI	PC All	Ret_Sal	Ret_Sal	Ret_Sal	9
10	Average Data	Dd ANDI	Average Data	PC All	NAIRU_GAP	PC All	% CU > Av	% CU > Av	10
11	NAIRU_GAP	**HP_Priors**	PC All	PC Data ROLL	CU ANDI	% CU > Av	PC All	NAIRU_GAP	11
12	**CD_GAP**	Average Data	**CD_GAP**	% CU > Av	% CU > Av	NAIRU_GAP	NAIRU_GAP	%GDP	12
13	Extra_H	**CD_GAP**	**HP_Priors**	**CD_GAP**	**CD_GAP**	**CD_GAP**	**CD_GAP**	**CD_GAP**	13
14	Money Gap	CU Fede	CU ANDI	CU ANDI	PC Data ROLL	**HP_Priors**	PC Data ROLL	PC All ROLL	14
15	PC Data ROLL	PC Stat ROLL	% CU > Av	Δ Occupied	**HP_Priors**	PC Data ROLL	PC All ROLL	**HP_Priors**	15
16	PC All	PC All	Δ Occupied	PC All ROLL	PC All ROLL	PC All ROLL	NAICU_GAP	PC Data ROLL	16
17	PC Stat ROLL	CU ANDI	Extra_H	Extra_H	NAICU_GAP	Gap Kalman	Extra_H	NAICU_GAP	17
18	CU Fede	PC All ROLL	PC Stat ROLL	**HP_Priors**	Gap Kalman	NAICU_GAP	%GDP	CU Fede	18
19	%GDP	Gap Kalman	%M3 - %GDP	NAICU_GAP	Δ Occupied	Extra_H	**HP_Priors**	Gap Kalman	19
20	**HP_Priors**	% CU > Av	PC All ROLL	PC Stat ROLL	Extra_H	%GDP	Δ Occupied	Δ Occupied	20
21	Gap Kalman	Money Gap	Gap Kalman	%M3 - %GDP	PC Stat ROLL	Δ Occupied	Gap Kalman	%M3 - %GDP	21
22	PC All ROLL	%GDP	Money Gap	Gap Kalman	%GDP	PC Stat ROLL	%M3 - %GDP	PC Stat ROLL	22
23	CU ANDI	FCI	NAICU_GAP	Money Gap	%M3 - %GDP	%M3 - %GDP	PC Stat ROLL	Extra_H	23
24	% CU > Av	**No Indicator**	%GDP	%GDP	Tr_B	Tr_B	Tr_B	MI	24
25	**No Indicator**	Extra_H	**No Indicator**	Tr_B	Money Gap	Money Gap	MI	Tr_B	25
26	Tr_B	MI	MI	MI	Net_Ext_Dd	Net_Ext_Dd	Net_Ext_Dd	Net_Ext_Dd	26
27	MI	Tr_B	PC Stat	Net_Ext_Dd	MI	MI	Money Gap	Money Gap	27
28	NAICU_GAP	PC Stat	Tr_B	**No Indicator**	**No Indicator**	**No Indicator**	**No Indicator**	PC Stat	28
29	PC Stat	NAICU_GAP	FCI	FCI	FCI	PC Stat	PC Stat	**No Indicator**	29
30	Energy_GAP	Average Stat	Average Stat	PC Stat	PC Stat	FCI	FCI	FCI	30
31	Average Stat	Energy_GAP	Net_Ext_Dd	%Cred - %GDP	%Cred - %GDP	Average Stat	Average Stat	Average Stat	31
32	%Cred - %GDP	Net_Ext_Dd	%Cred - %GDP	Energy_GAP	Average Stat	Energy_GAP	Energy_GAP	Energy_GAP	32
33	Net_Ext_Dd	%Cred - %GDP	Energy_GAP	Average Stat	Energy_GAP	%Cred - %GDP	%Cred - %GDP	HP	33
34	HP	HP	HP	HP	HP	HP	HP	%Cred - %GDP	34
35	BP	BP	BP	BP	BP	BP	BP	BP	35