Estimating an Output Gap Indicator Using Business Surveys and Real Data

Norberto Rodríguez N.*

José Luis Torres T.

Andrés Velasco M.

Abstract

An accurate estimation of the output gap is crucial for conducting monetary policy under an inflation targeting regime. In Colombia's Central Bank various measurements are estimated using different strategies. Unfortunately, since the output gap is unobservable, there is always great uncertainty on any of these alternative estimations. Because of this, in order to improve the analysis, specialists at the Inflation Department regularly follow business surveys and real data. Summarizing all the information available into one output gap estimation is necessary for the policy recommendations and is problematic. Until recently, the weights assigned to each measure and to the surveys in the analysis, were based solely on the opinion of the specialists, which could possibly lead to an omitted variable problem. To overcome this, in this paper an output gap indicator is estimated as the unobserved factor from the available data set of alternative measures. The indicator is calculated using static principal components analysis (PCA), which summarizes the information contained in the data set and excludes measurement errors. The quality of the output gap indicator is then evaluated by its out of sample predictive ability of the core non-tradable inflation in Colombia, using a hybrid Phillips Curve. The results suggest as expected, that the output gap indicator is better for identifying demand pressures in the economy than any of the individual measures. Moreover, the out of sample forecasts were further improved when the measures that come from traditional statistical filters on real data were excluded from the estimation of the indicator. This confirms the importance of the business surveys for an accurate estimation of Colombia's output gap, despite the fact that the industry only accounts for 15% of the GDP.

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

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

* Professionals from the Research Division at Colombia's Central Bank. Norberto Rodriguez is also a professor at Universidad Nacional de Colombia.

1. Introduction

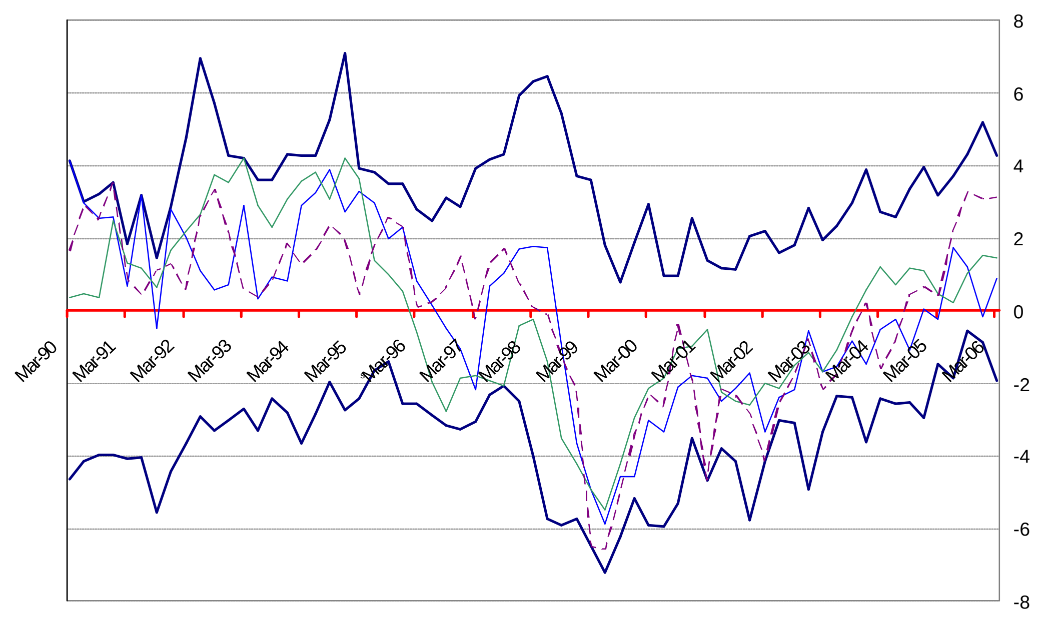
Colombia's Central Bank conducts monetary policy using Inflation Targeting since 1999, after exchange rate bands were abandoned. Under this regime, the interest rate that is charged to the commercial banks for their overnight liquidity demands depends on the double relation between the expected future inflation and the inflation target, and the GDP and the non inflationary product. Therefore, monetary policy depends critically on inflation forecasts[1], 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)[2]. 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)[3]: 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[4], 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.

[1] 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.
[2] 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.
[3] 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.
[4] 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).

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 diverse methodologies, in practice this implies 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 Graph 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.

Graph 1: Output Gap According to Various Measurements



Source: ANDI, FEDESARROLLO, Central Bank

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 evaluation of the out of sample forecasts for the core inflation that are produced using these measures as activity indicators in a hybrid Phillips Curve[5].

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 proposed. 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.

2. 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, 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)[6].

2.1. 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

[5] Such as the one used in the TMM, which includes rational (forward looking of future inflation) and adaptative expectations (based on the lagged inflation).
[6] Cobo (2004) presents an exhaustive review of the different methodologies that have been applied in Colombia.

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 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[7]. 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.

2.2. 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.

[7] 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[8]. 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[9].

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 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

[8] Some of the most important are: Stock et. al. (1999, 2002 and 2004) and Giannone et. al. (2004).
[9] Several authors have proved the empirical instability of the Phillips Curve and commented it potential causes and consequences. Two examples are: Deutsche Bank (2005) for the US and King (2005) for the UK.

formats. They also point that the method does not impose any economic structure and solves in a simple and efficient manner the main problems of the low dimensional forecast models that are traditionally used[10]. 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[11].

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[12].

The common factors may also be estimated using the dynamic methodology in stages developed by Forni et. al. (2000)[13]. 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

[10] 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.
[11] For the same reason, the method does not suffer too much from the end of sample bias of traditional statistical filters.
[12] 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.
[13] Some older dynamic alternatives are Sargent and Sims (1977) and Geweke (1977).

designed to capture them[14]. 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 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 autocovarizes that should be considered for constructing the spectral density matrix and for how many domain frequencies the proper dynamic values (*eigenvalues*) will be estimated[15].

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 once 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[16]. Since the dynamic methodology is more complicated and is by no means

---

[14] 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.
[15] 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.
[16] This is why a high R^2 is not enough to know if the estimated factor truly summarizes the information from the series.

superior to its static counterpart, we decided to discard the former and concentrate in the latter for this work.

2.3. 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)[17], the economic activity index of the Chicago FED (CFNAI)[18], forecasts of the returns of treasury bonds[19], the estimation of inputs for dynamic general equilibrium models[20] and the study of the macroeconomic comovements of the G-7 countries[21]. 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*[22] is solved and the response of the output gap changes to the right sign. Stock and Watson

---

[17] Calculated by the Center for Economic Policy Research (CEPR), using dynamic principal components based on the work of Altísimo et. al. (2001).
[18] Using PCA following Stock et. al. (1999)
[19] Ludvigson and Ng (2005) using estimated components with PCA from financial and activity variables.
[20] Boivin and Giannoni (2005) which use dynamic factor analysis.
[21] Kose et. al. (2005), using a dynamic Bayesian model of latent factors.
[22] 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.

(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.

3. 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[23] 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 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) $$x_{i,t} = l_{i,1} f_{1,t} + ... + l_{i,r} f_{r,t} + e_{i,t} = \Lambda_i^{'} F_t + e_{it}$$

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

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[24].

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 $\left(x_{i,t} - l_i f_{i,t}\right)^2$. More over, the estimators of $\hat{F}_t$ must minimize the objective function (3):

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

[24] This 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.

Under the assumption that there are r common factor, the optimal estimators of the factors turns 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[25].

In order to choose the number of q factors of that must be used to forecast Y_{t+1}, Stock and Watson (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[26]. The lags were strategically chosen to minimize the mean square error of the forecasts.

---

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

[26] 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.

4. 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[27].

4.1. The output gap measures used for the estimation

Bearing this tradeoff in mind, we employed for the estimation of the output gap indicator twenty output gap measures or *proxies*, which are periodically followed by the inflation staff at Colombia's Central Bank[28]. In order to have a balanced panel, the data set goes from March 1990 to March 2006. The measures and *proxies* employed are:

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.

[27] 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.

[28] Some references for this measures are Julio (2001), Cobo (2004), Nigrinis (2003)and López and Misas (1998).

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 industry 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. HP: the Hodrick and Prescott filter.

xv. BP: the Band Pass filter.

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

xvii. HP_*Priors*: the Hodrick and Prescott filter with *priors*[29].

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

xix. 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).

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

[29] 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.

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

	Acronym	Indicator	Source
1	Dd_ANDI	% of entrepreneurs whothink 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 non-regulated energy demandand the long run demand	CB Estimations
20	PC_ALL	Principal Component estimated with all the series using all the available data	Authors Estimations
21	PC_ALL_ROLL	Principal Component estimated with all the series using rolling windows of 32 quarters	Authors Estimations
22	PC_DATA	Principal Component estimated with the series from the data group using all the available data	Authors Estimations
23	PC_DATA_ROLL	Principal Component estimated with the series from the data group using rolling windows of 32 quarters	Authors Estimations
24	PC_STAT	Principal Component estimated with the series from the statistical estimates using all the available data	Authors Estimations
25	PC_STAT_ROLL	Principal Component estimated with the series from the statistical estimates using using rolling windows of 32 quarters	Authors Estimations
26	Monetary Index	A monetary index estimated as the first principal component from series 12 and 13	Authors Estimations
27	FCI	A Financial Conditions Index estimated as the first prncipal component from various financial series	Authors Estimations

Table 1 includes a summary of the measures used, its acronyms, the source of the data and a brief definition. In Appendix 1 are presented the graphs of each of the measures or *proxies* of the output gap considered for the estimation of the indicator[30]. All of them show the expansion of the economy in the first part of the past decade until 1998 and then they show 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

[30] 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.

is generally above 0.8 implying that the changes in all of the series are similar even though their level varies significantly.

4.2. The estimation

The twenty 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, 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 and the energy gap.

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. The gaps were constructed as the difference with the long run average of the 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[31].

With the twenty 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 weight 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[32]. 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

[31] 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.
[32] Among others, Misas and Melo (2004) suggest that the Colombian economy suffered from structural changes at the end of the past decade.

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 with the estimated group. The explained variance that is captured by the first PC is also presented for each case. Figure 1 presents the indicators estimated with all of the series in the static and in the rolling windows exercise. Figure 2 shows the same graphs for the indicators estimated with the data group and Figure 3 for the indicators that come from the group of the statistical estimations.

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 FFR and the gap of the real valuations of Colombia's stock index (IGBC).[33]

[33] 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).

Table 2: Weights for each measure in the first estimated static PC for each group

Proxy or Measure	GROUP		
	DATA	STATISTICS	ALL
Dd_ANDI	11%		6%
CU_ANDI	11%		7%
Tr_B	4%		4%
Extra_H	9%		6%
Cap vs. Dd	11%		6%
CU_FEDE	11%		7%
% CU > Av	8%		5%
Net_Ext_Dd	4%		4%
Lics	10%		6%
Ret_Sal	9%		5%
?Occupied	5%		2%
%Cred - %GDP	4%		3%
%M3 - %GDP	3%		2%
HP		15%	4%
BP		12%	4%
CD_GAP		18%	7%
HP_Priors		17%	7%
NAIRU_GAP		16%	7%
NAICU_GAP		14%	6%
Energy_GAP		10%	3%
Explained Variance	58%	67%	59%

Figure 1: First PC for all the series in the static and rolling exercise

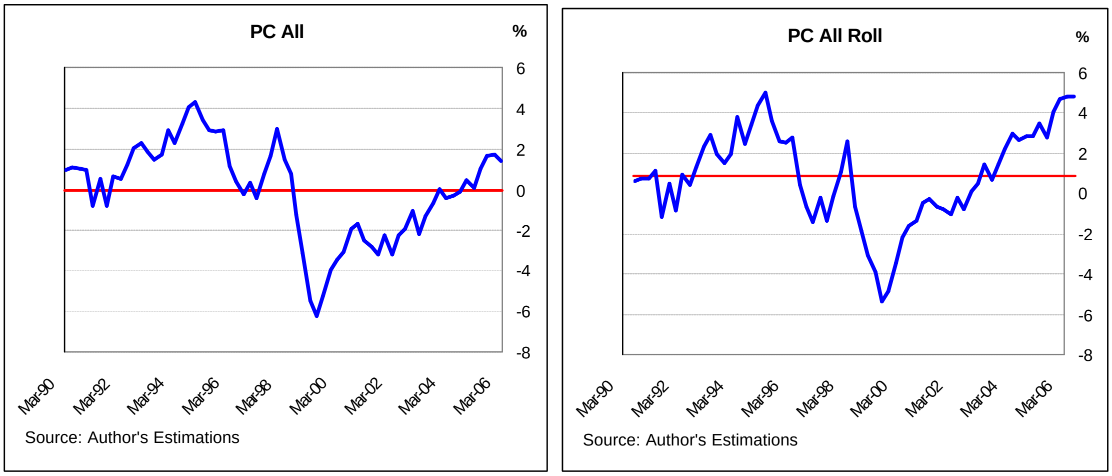
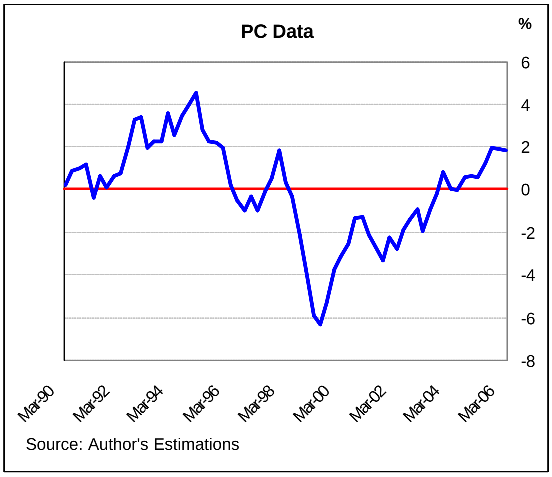


Figure 2: First PC for the group of data in the static and rolling exercise



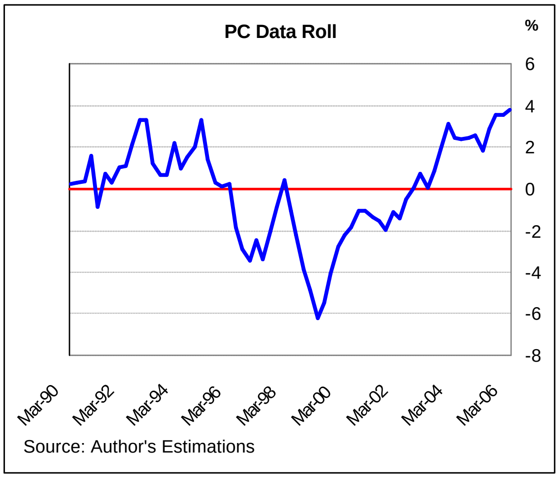
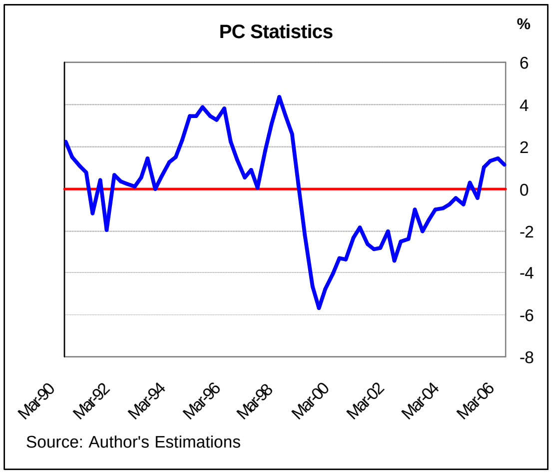
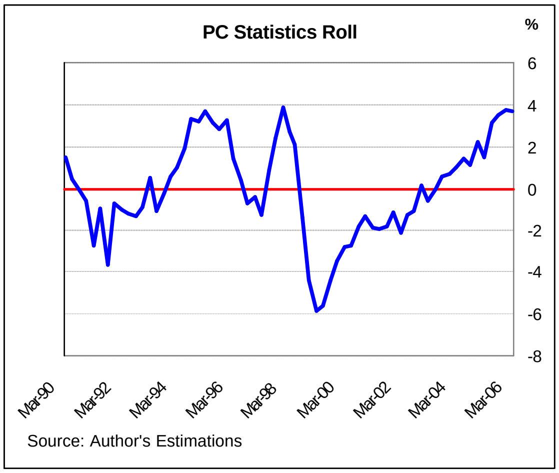


Figure 3: First PC for the group of filters in the static and rolling exercise





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

Since the output gap is not directly observable, by using PCA we only augmented the initial problem. Because we started with twenty output gap measures and *proxie*s and we ended up with twenty-eight 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 and to the one shown earlier in equation 2:

(4) $$p_t^c = g(L)p_{t-1}^c + ap_t^E + \partial_1(L) f_{1,t} + u_t,$$

Where $g(L)p_{t-1}^c$ includes selected lags of the non-tradable core inflation, p_t^E is the 12M expected total inflation as measured by the central banks survey, p_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 twenty-two 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 $a + g(1)$ 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 twenty-two series that are being evaluated and the optimal lags were chosen with a stepwise methodology.

In Appendix 2 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 Appendix 3 are presented the results of the evaluations organized by the mean average percentage error (MAPE). 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[34]. 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 average percentage error is 1,35% for PC_ data and more than double for the HP gap (2,92%).

In Appendix 4 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 specially for longer horizons and is highly

[34] 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.

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 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. 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.

5. 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 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). Additionally 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.

References

Altissimo, F., A. Bassanetti, R. Cristadoro, M. Forni, M. Lippi, L. Reichlin and G. Veronese (2001). "EUROCOIN: A Real Time Coincident Indicator of the Euro Area Business Cycle". CEPR Discussion Paper Series, No. 3108.

Bai, J. and S. Ng (2000). "Determining the Number of Factors in Approximate Factor Model". Econometrica, No. 70.

_____________ (2005). "Confidence Intervals for Diffusion Index Forecasts and Inferences for Factor or Augmented Regressions" Econometrica, Forthcoming.

Bernanke, B. and J. Boivin (2003). "Monetary Policy in a Data-Rich Environment". Journal of Monetary Economics. Vol. 50, No. 3.

Boivin, J. and S. Ng (2003). "Are More Data Always Better for Factor Analysis?". NBER Working Paper Series, No. 9829.

_______________ (2005). "Understanding and Comparing Factor-Based Forecast". NBER Working Paper Series, No. 11285.

Boivin, J. and M. Gianonni (2005). "DSGE Models in a Data Rich Environment" Unpublished Paper. Columbia University.

Cobo, A. L. (2004). "Output Gap in Colombia: An Eclectic Approach". Borradores de Economía No. 327. Banco de la República.

Deutsche Bank (2005). "Analysis of Coefficient Stability in Simple Inflation Models" US Economics Weekly. Global Markets Research. Marzo 11.

Favero, C., M. Marcellino, and F. Neglia (2005). "Principal Components at Work: The Empirical Analysis of Monetary Policy with Large Datasets". Journal of Applied Economics. Vol. 20.

Fisher, J. (2000). “Forecasting Inflation with a lot of Data”. Chicago FED Letter. Federal Reserve Bank of Chicago, No. 151.

Forni, M., M Hallin, M. Lippi and L. Reichlin (2000). “The Generalized Factor Model: A Identification and Estimation” The Review of Economics and Statistics, No. 82.

Gauthier, C., C. Graham, and Y. Liu (2004). “Financial Conditions Indexes for Canada”. Working Paper No. 04-22. Bank of Canada.

Geweke, J. (1977). “The Dynamic Factor Analysis of Economic Time Series”. Latent Variables in Socio-Economic Models. Edit. North-Holland. Amsterdam.

Gianonne, D., L. Reichlin and D. Samall (2005). “Nowcasting GDP and Inflation: The Real-Time Informational Content of Macroeconomic Data Releases” Finance and Economics Discussion Series. Federal Reserve Board, Washington D.C. No. 42.

Gómez, J., J. D. Uribe, and H. Vargas (2002). “The Implementation of Inflation Targeting in Colombia” Borradores de Economía No. 202. Banco de la República.

Hendry, D.F. and G.E. Mizon (2005), Forecasting in the Presence of Structural Breaks and Policy Regime Shifts. In Identification and Inference in Econometric Models: Festschrift in Honor of T.J. Rothenberg, edited by D.W. Andrews, J.L. Powell, P.A. Ruud and J. Stock, Cambridge University Press

Julio, J. M. (2001). “How Uncertain are NAIRU Estimates in Colombia?”. Borradores de Economía No. 184. Banco de la República.

Kapetanios, G. and M. Marcellino (2003). “A Comparison of Estimation Methods for Dynamic Factor Models of Large Dimensions”. Queen Mary, University of London, Department of Economics. Working Papers, No. 489.

King, M. (2005). “Monetary Policy: Practice Ahead of Theory” Mais Lecture. Bank of England.

Kose, M., C. Otrok, and C. Whiteman (2005). "Understanding the Evolution of World Business Cycles". IMF Working Paper, No. 211.

Lansing, K. (2002). "Can the Phillips Curve Help Forecast Inflation?". FRBSF Economic Letter. Federal Reserve Bank of San Francisco, No. 29.

Ludvigson, S. and S. Ng (2005). "Macro Factors in Bond Risk Premia". NBER Working Paper Series, No. 11703.

López, M. (2004). "Efficient Policy Rule for Inflation Targeting in Colombia" Revista de Ensayos Sobre Política Económica. Banco de la República No. 45.

López, E. and M. Misas (1998). "Un examen empírico de la Curva de Phillips en Colombia". Revista de Ensayos Sobre Política Económica, No. 34.

McCallum, B. (2001). "Should Monetary Policy Respond Strongly to Output Gaps?". NBER Working Paper No. 8226.

Melo, L., F. Nieto, C. Posada, Y. R. Betancourt, y J. Barón. (2001). "Un índice coincidente para la actividad económica colombiana". Borradores de Economía No. 195. Banco de la República.

Misas, M. and L. Melo (2004). "Modelos Estructurales de Inflación en Colombia: Estimación a través de Mínimos Cuadrados Flexibles". Borradores de Economía No. 284. Banco de la República.

Nigrinis, M. (2003). "Es lineal la Curva de Phillips en Colombia". Borradores de Economía No. 282. Banco de la República.

Modelos Macroeconómicos (2004). "Bienes transables, no transables y regulados en el MMT". Mimeo. Banco de la República.

Peña S. (2002). Análisis de Datos Multivariantes. McGraw Hill, Madrid.

Peña S., D. and P. Poncela (2006) “Nonstationary Dynamic Factor Analysis” Journal of Statistical Planning and Inference, Volume 136, Issue 4.

Sargent, T and C. Sims (1977). “Business Cycle Modeling Without Pretending to Have to Much a-priori Economic Theory”. New Methods in Business Cycle Research. Federal Reserve Bank of Minneapolis.

Stock, J. and M. Watson (1989). “New Indexes of Coincident and Leading Economic Indicator”. NBER Macroeconomics Annual.

__________________ (1991). “A Probability Model of the Coincident Economic Indicators”. In The Leading Economic Indicators: New Approaches and Forecasting Records. Cambridge University Press.

__________________ (1998). “Diffusion Indexes”. NBER Working Papers Series, No. 6702.

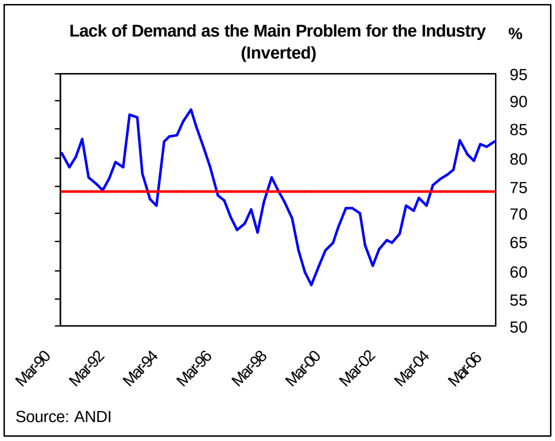
__________________ (1999). “Forecasting Inflation”. Journal of Monetary Economics, Vol. 44.

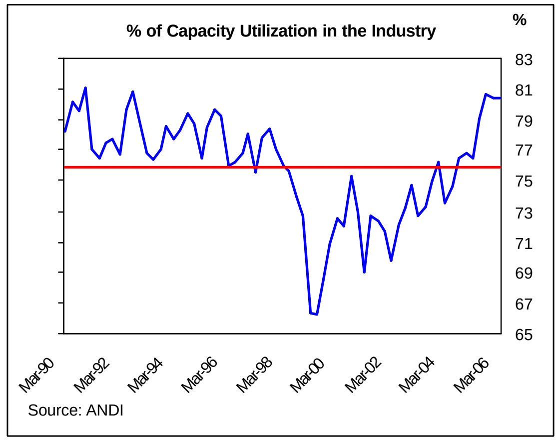
__________________ (2002). “Macroeconomics Forecasting Using Diffusion Indexes”. Journal of Business and Economic Statistics. 20:2.

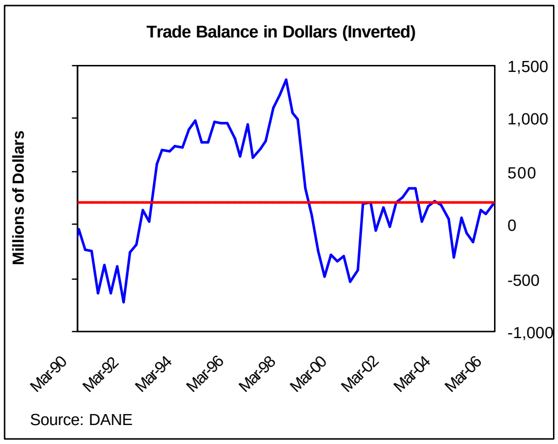
__________________ (2004). “Forecasting with Many Predictors”. In Handbook of Economic Forecasting.

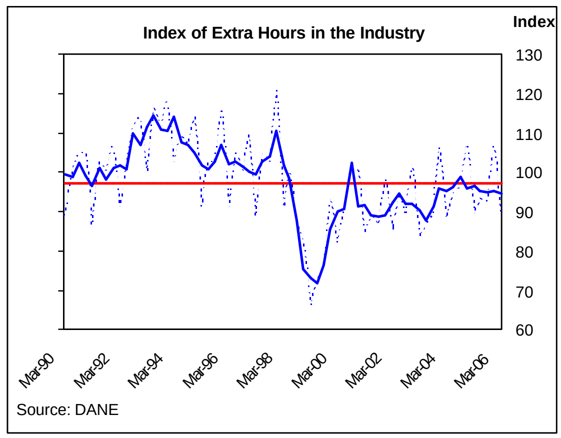
Watson, M. (2000). “Macroeconomic Forecasting Using Many Predictors”. Mimeo Princeton University.

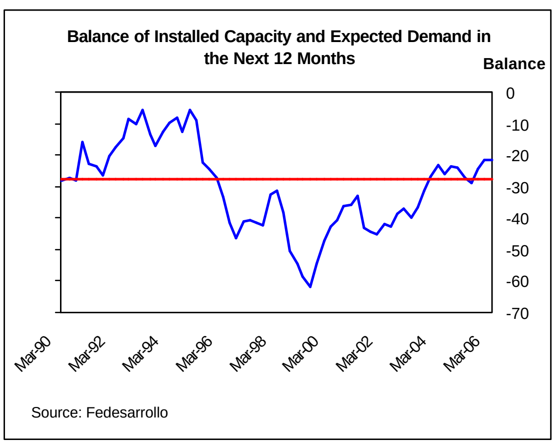
Appendix 1: Different measures and *proxies* for the output gap in Colombia

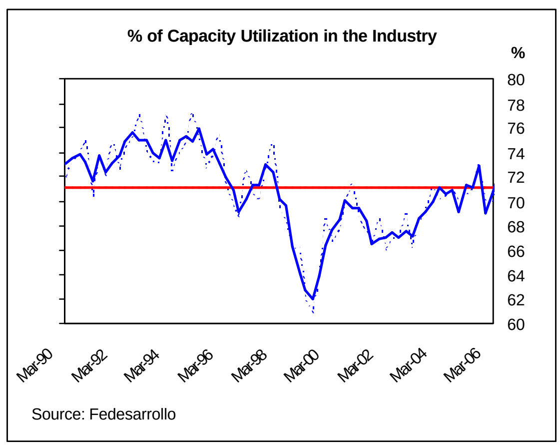


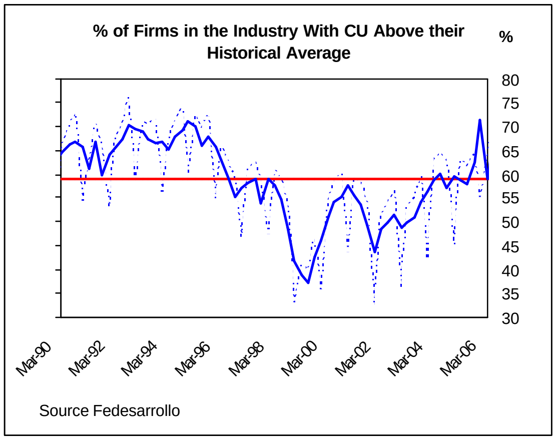


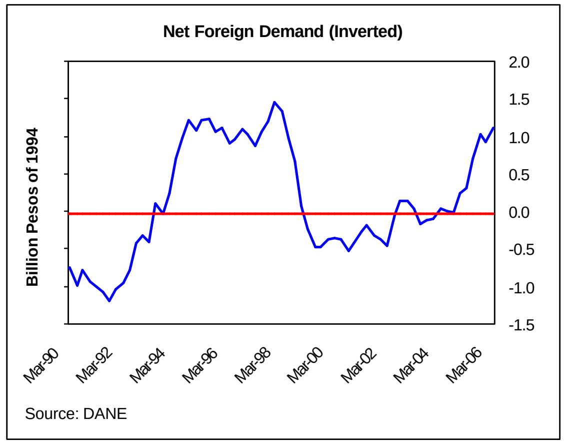


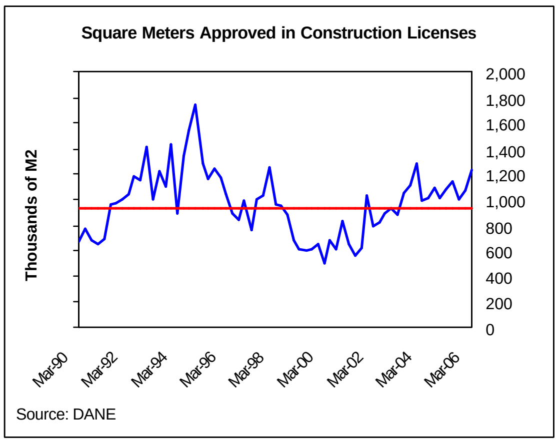


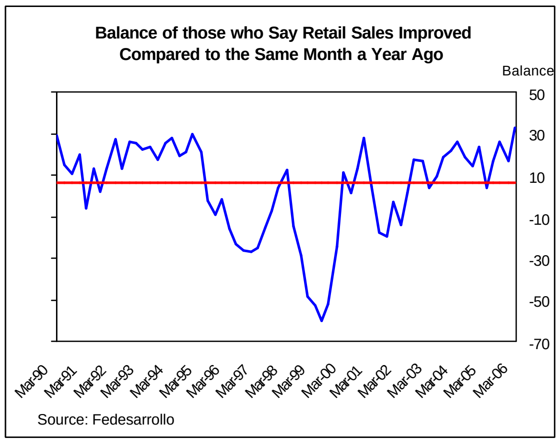


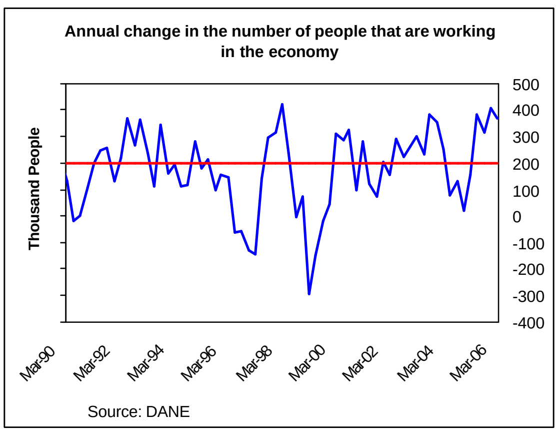


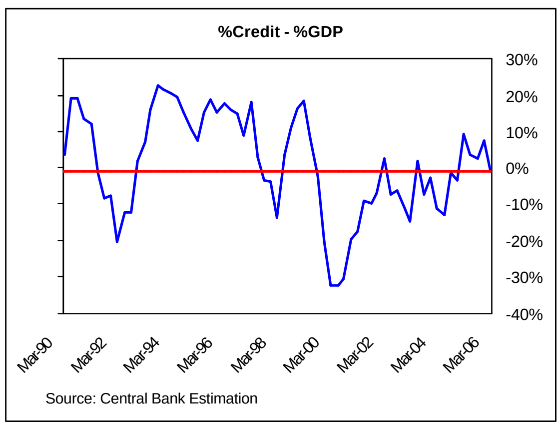

% of Firms in the Industry With CU Above their Historical Average
%
80
75
70
65
60
55
50
45
40
35
30
Mar-90
Mar-92
Mar-94
Mar-96
Mar-98
Mar-00
Mar-02
Mar-04
Mar-06
Source Fedesarrollo

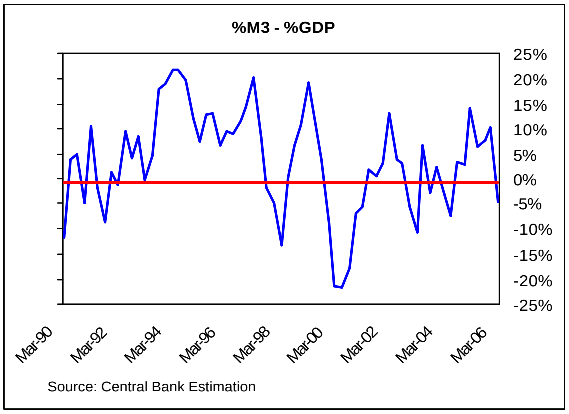

Net Foreign Demand (Inverted)
Billion Pesos of 1994
2.0
1.5
1.0
0.5
0.0
-0.5
-1.0
-1.5
Mar-90
Mar-92
Mar-94
Mar-96
Mar-98
Mar-00
Mar-02
Mar-04
Mar-06
Source: DANE

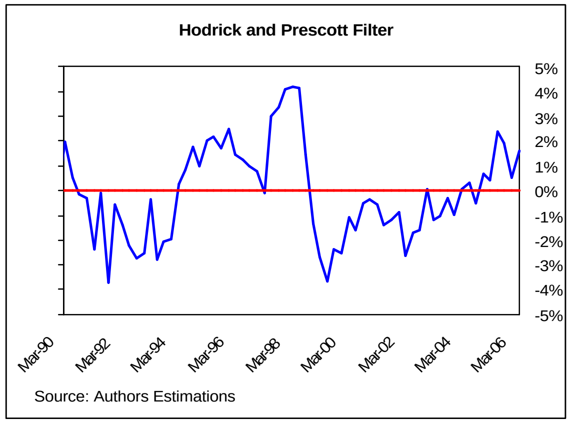

Square Meters Approved in Construction Licenses
Thousands of M2
2,000
1,800
1,600
1,400
1,200
1,000
800
600
400
200
0
Mar-90
Mar-92
Mar-94
Mar-96
Mar-98
Mar-00
Mar-02
Mar-04
Mar-06
Source: DANE

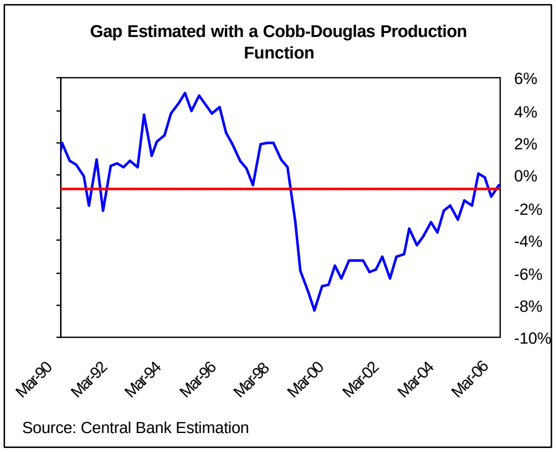

Balance of those who Say Retail Sales Improved Compared to the Same Month a Year Ago
Balance
50
30
10
-10
-30
-50
-70
Mar-90
Mar-91
Mar-92
Mar-93
Mar-94
Mar-95
Mar-96
Mar-97
Mar-98
Mar-99
Mar-00
Mar-01
Mar-02
Mar-03
Mar-04
Mar-05
Mar-06
Source: Fedesarrollo

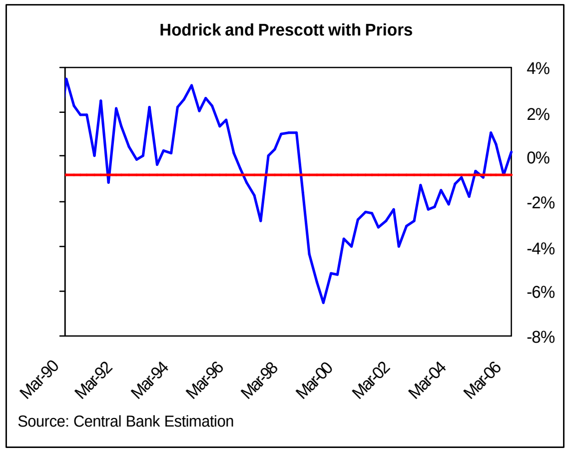

Annual change in the number of people that are working in the economy
Thousand People
500
400
300
200
100
0
-100
-200
-300
-400
Mar-90
Mar-92
Mar-94
Mar-96
Mar-98
Mar-00
Mar-02
Mar-04
Mar-06
Source: DANE

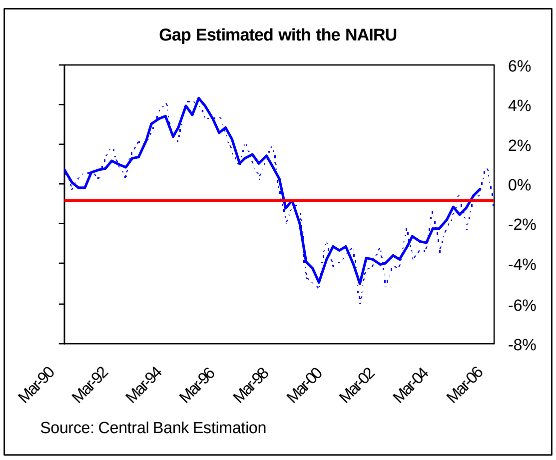

%Credit - %GDP
30%
20%
10%
0%
-10%
-20%
-30%
-40%
Mar-90
Mar-92
Mar-94
Mar-96
Mar-98
Mar-00
Mar-02
Mar-04
Mar-06
Source: Central Bank Estimation

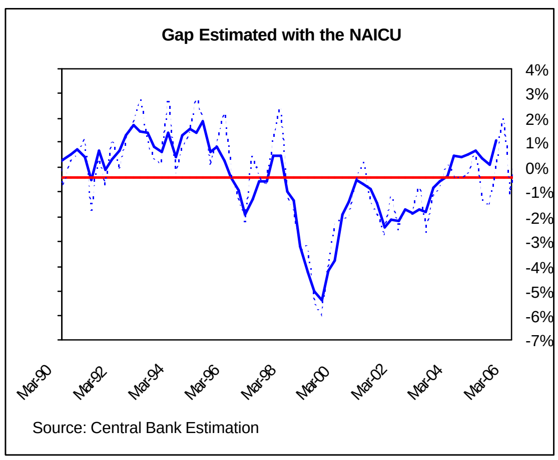

%M3 - %GDP
25%
20%
15%
10%
5%
0%
-5%
-10%
-15%
-20%
-25%
Mar-90
Mar-92
Mar-94
Mar-96
Mar-98
Mar-00
Mar-02
Mar-04
Mar-06
Source: Central Bank Estimation

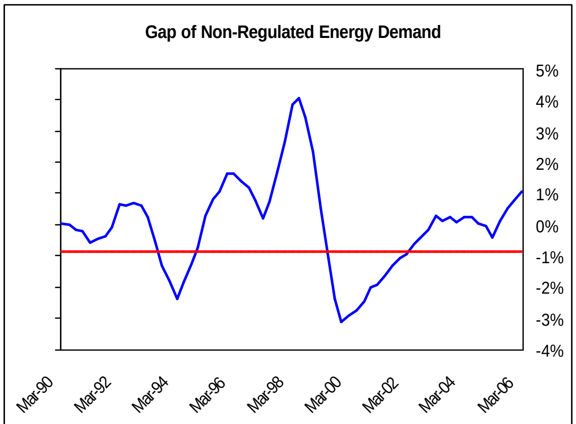

Hodrick and Prescott Filter
5%
4%
3%
2%
1%
0%
-1%
-2%
-3%
-4%
-5%
Mar-90
Mar-92
Mar-94
Mar-96
Mar-98
Mar-00
Mar-02
Mar-04
Mar-06
Source: Authors Estimations


Gap Estimated with a Cobb-Douglas Production Function
6%
4%
2%
0%
-2%
-4%
-6%
-8%
-10%
Mar-90
Mar-92
Mar-94
Mar-96
Mar-98
Mar-00
Mar-02
Mar-04
Mar-06
Source: Central Bank Estimation

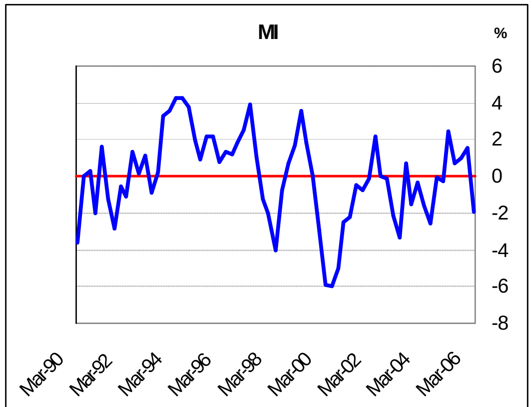

Hodrick and Prescott with Priors
4%
2%
0%
-2%
-4%
-6%
-8%
Mar-90
Mar-92
Mar-94
Mar-96
Mar-98
Mar-00
Mar-02
Mar-04
Mar-06
Source: Central Bank Estimation


Gap Estimated with the NAIRU
6%
4%
2%
0%
-2%
-4%
-6%
-8%
Mar-90
Mar-92
Mar-94
Mar-96
Mar-98
Mar-00
Mar-02
Mar-04
Mar-06
Source: Central Bank Estimation

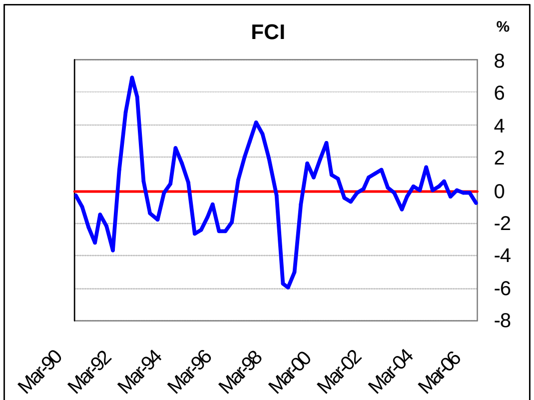

Gap Estimated with the NAICU
4%
3%
2%
1%
0%
-1%
-2%
-3%
-4%
-5%
-6%
-7%
Mar-90
Mar-92
Mar-94
Mar-96
Mar-98
Mar-00
Mar-02
Mar-04
Mar-06
Source: Central Bank Estimation



Source: Central Bank Estimation



Source: Author's Estimations



Source: Author's Estimations

Appendix 2: Selected Hybrid Phillips Curves for each of the output gap measures (Mar-98 _ Mar-06)

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

Appendix 3: Forecast evaluation for each measure for various horizons

Out of Sample Forecast Evaluation for Various Horizons*

Horizon 1 N=33	ME	MAE	MAPE	RMSE	RMSPE	UTHEIL
? Occupied	-0.79	1.20	23%	1.79	36%	0.98
PC Data	-0.16	1.19	25%	1.60	39%	0.87
Lics	-0.34	1.47	32%	1.81	42%	0.99
Cap vs. Dd	-0.32	1.14	26%	1.53	44%	0.84
%M3 - %GDP	-0.69	1.28	29%	1.80	44%	0.98
Ret_Sal	-0.56	1.30	29%	1.73	44%	0.95
Dd_ANDI	-0.38	1.28	28%	1.72	48%	0.94
FCI	-0.87	1.37	29%	1.85	49%	1.01
NAIRU_GAP	-0.27	1.29	28%	1.79	50%	0.98
CD_GAP	-0.46	1.33	28%	1.90	50%	1.04
Extra_H	-0.46	1.29	28%	1.73	51%	0.95
PC_DATA_ROLL	-0.44	1.43	33%	1.78	51%	0.97
PC All	-0.50	1.28	28%	1.76	51%	0.96
PC_STAT_ROLL	-0.86	1.36	30%	1.88	52%	1.03
CU_FEDE	-0.15	1.12	26%	1.62	53%	0.89
HP_Priors	-0.55	1.27	28%	1.78	54%	0.98
PC_ALL_ROLL	-0.70	1.41	33%	1.78	55%	0.98
CU_ANDI	-0.30	1.36	30%	1.82	55%	0.99
% CU > Av	-0.32	1.32	30%	1.82	55%	0.99
Tr_B	-0.85	1.55	33%	2.00	57%	1.09
MI	-0.73	1.40	33%	1.96	60%	1.07
NAICU_GAP	-0.40	1.25	29%	1.75	61%	0.96
PC_STAT	-0.85	1.39	32%	1.93	61%	1.06
Energy_GAP	-0.72	1.35	34%	1.76	62%	0.96
%Cred - %GDP	-0.91	1.34	33%	1.90	65%	1.04
Net_Ext_Dd	-0.95	1.54	37%	1.98	67%	1.09
HP	-0.83	1.39	34%	1.88	69%	1.03
BP	-1.38	1.77	40%	2.75	85%	1.46

Horizone 6 N=28	ME	MAE	MAPE	RMSE	RMSPE	UTHEIL
PC Data	0.18	1.14	26%	1.42	32%	0.37
Cap vs. Dd	-0.35	1.18	28%	1.58	38%	0.42
CU_ANDI	0.10	1.28	31%	1.68	46%	0.44
Lics	-0.19	1.96	44%	2.25	50%	0.59
Dd_ANDI	-0.46	1.53	37%	1.93	50%	0.51
CU_FEDE	-0.04	0.92	26%	1.21	50%	0.32
Ret_Sal	-1.49	1.95	43%	2.35	52%	0.62
PC All	-0.32	0.88	26%	1.21	53%	0.32
% CU > Av	-0.33	1.28	32%	1.64	53%	0.43
NAIRU_GAP	0.15	1.13	31%	1.43	54%	0.38
CD_GAP	-0.30	0.94	28%	1.27	57%	0.33
HP_Priors	-1.01	1.26	35%	1.76	63%	0.47
PC_DATA_ROLL	-0.89	2.32	51%	2.84	64%	0.75
PC_ALL_ROLL	-1.23	1.94	48%	2.41	66%	0.64
NAICU_GAP	-0.41	0.99	30%	1.43	68%	0.38
Extra_H	-0.76	1.21	36%	1.67	72%	0.44
? Occupied	-2.77	2.77	63%	3.32	73%	0.88
PC_STAT_ROLL	-1.91	1.91	50%	2.42	74%	0.64
%M3 - %GDP	-1.76	2.29	55%	3.27	81%	0.86
Tr_B	-1.82	2.04	57%	2.65	88%	0.70
Net_Ext_Dd	-2.47	2.52	68%	2.84	96%	0.75
MI	-2.60	2.74	67%	4.00	99%	1.06
PC_STAT	-2.12	2.21	62%	2.86	111%	0.75
FCI	-2.45	2.57	67%	3.52	112%	0.93
Energy_GAP	-3.36	3.46	89%	4.54	122%	1.20
%Cred - %GDP	-3.77	3.77	94%	4.65	123%	1.23
HP	-2.76	2.91	81%	3.53	137%	0.93
BP	-5.54	6.06	153%	8.13	242%	2.07

Horizon 4 N=30	ME	MAE	MAPE	RMSE	RMSPE	UTHEIL
PC Data	-0.11	1.39	29%	1.88	37%	0.56
Cap vs. Dd	-0.57	1.30	29%	1.81	41%	0.53
Lics	-0.47	2.30	49%	2.59	54%	0.77
CU_FEDE	-0.24	1.15	28%	1.78	57%	0.53
NAIRU_GAP	-0.24	1.44	34%	2.05	57%	0.60
Ret_Sal	-1.43	2.10	47%	2.60	59%	0.77
Dd_ANDI	-0.75	1.82	41%	2.46	60%	0.73
PC All	-0.67	1.26	31%	1.98	61%	0.58
PC_DATA_ROLL	-0.96	2.26	51%	2.73	63%	0.81
% CU > Av	-0.61	1.62	37%	2.40	66%	0.71
CD_GAP	-0.62	1.38	34%	2.14	67%	0.63
CU_ANDI	-0.32	1.74	39%	2.53	67%	0.75
? Occupied	-2.44	2.53	54%	3.48	69%	1.03
PC_ALL_ROLL	-1.23	1.88	46%	2.47	73%	0.73
Extra_H	-0.96	1.51	38%	2.21	74%	0.65
HP_Priors	-1.23	1.62	39%	2.63	76%	0.78
NAICU_GAP	-0.55	1.23	33%	1.97	77%	0.58
PC_STAT_ROLL	-1.98	2.05	48%	3.11	79%	0.92
%M3 - %GDP	-1.80	2.41	55%	3.32	80%	0.98
Tr_B	-1.81	2.34	57%	3.11	92%	0.92
MI	-2.33	2.56	59%	3.83	93%	1.13
Net_Ext_Dd	-2.37	2.55	65%	2.97	95%	0.88
FCI	-2.25	2.55	60%	3.63	99%	1.07
PC_STAT	-2.09	2.19	55%	3.32	106%	0.98
%Cred - %GDP	-2.88	2.94	71%	3.98	107%	1.17
Energy_GAP	-2.50	2.90	73%	3.77	111%	1.11
HP	-2.30	2.62	70%	3.40	133%	1.00
BP	-4.84	5.25	125%	7.54	222%	2.15

Horizone 8 N=26	ME	MAE	MAPE	RMSE	RMSPE	UTHEIL
Cap vs. Dd	-0.09	0.97	24%	1.32	33%	0.34
PC Data	0.32	1.15	28%	1.44	36%	0.37
CU_ANDI	0.44	1.15	29%	1.40	41%	0.36
Dd_ANDI	-0.20	1.36	35%	1.65	48%	0.42
PC All	-0.28	0.93	27%	1.26	49%	0.32
Lics	-0.09	1.93	44%	2.26	51%	0.58
Ret_Sal	-1.24	1.91	44%	2.18	51%	0.56
% CU > Av	-0.02	1.11	31%	1.32	52%	0.34
NAIRU_GAP	0.32	1.06	30%	1.37	54%	0.35
CD_GAP	-0.33	1.02	30%	1.36	60%	0.35
PC_ALL_ROLL	-1.38	2.06	50%	2.56	64%	0.65
HP_Priors	-0.80	1.08	33%	1.42	65%	0.36
PC_DATA_ROLL	-0.80	2.44	55%	2.97	67%	0.76
NAICU_GAP	-0.46	1.07	32%	1.53	68%	0.39
CU_FEDE	0.04	0.87	28%	1.28	68%	0.33
? Occupied	-2.79	2.79	67%	3.01	74%	0.77
%M3 - %GDP	-1.40	2.12	52%	3.06	78%	0.78
PC_STAT_ROLL	-1.78	1.78	51%	2.15	79%	0.55
Extra_H	-0.52	0.97	33%	1.53	84%	0.39
MI	-2.32	2.43	62%	3.41	89%	0.87
Tr_B	-2.00	2.54	68%	3.08	92%	0.79
Net_Ext_Dd	-2.56	2.66	72%	2.97	98%	0.76
PC_STAT	-2.02	2.12	63%	2.80	118%	0.71
FCI	-2.55	2.60	72%	3.51	121%	0.90
Energy_GAP	-3.95	4.05	106%	5.22	143%	1.33
HP	-3.29	3.55	98%	4.04	148%	1.03
%Cred - %GDP	-4.39	4.39	115%	5.06	149%	1.29
BP	-5.44	6.04	164%	7.80	258%	1.91

*The evaluation corresponds to annual non-tradable core inflation forecasts made with a hybrid Phillips Curve from mar-98 to mar-06.

Appendix 4: Summary of the best output gap measures for various horizons

Summary of the Performance of the Measures for Various Horizons*

Ranking	1 Qtr.	2 Qtr.	3 Qtr.	4 Qtr.	Ranking
1	? Occupied	PC Data	PC Data	PC Data	1
2	PC Data	Ret_Sal	Cap vs. Dd	Cap vs. Dd	2
3	Lics	Cap vs. Dd	Ret_Sal	Lics	3
4	Cap vs. Dd	? Occupied	CU_FEDE	CU_FEDE	4
5	%M3 - %GDP	Lics	Lics	NAIRU_GAP	5
6	Ret_Sal	%M3 - %GDP	Dd_ANDI	Ret_Sal	6
7	Dd_ANDI	NAIRU_GAP	NAIRU_GAP	Dd_ANDI	7
8	FCI	PC_DATA_ROLL	PC_DATA_ROLL	PC All	8
9	NAIRU_GAP	Dd_ANDI	PC All	PC_DATA_ROLL	9
10	CD_GAP	HP_Priors	CD_GAP	% CU > Av	10
11	Extra_H	CD_GAP	HP_Priors	CD_GAP	11
12	PC_DATA_ROLL	CU_FEDE	CU_ANDI	CU_ANDI	12
13	PC All	PC_STAT_ROLL	% CU > Av	? Occupied	13
14	PC_STAT_ROLL	PC All	? Occupied	PC_ALL_ROLL	14
15	CU_FEDE	CU_ANDI	Extra_H	Extra_H	15
16	HP_Priors	PC_ALL_ROLL	PC_STAT_ROLL	HP_Priors	16
17	PC_ALL_ROLL	% CU > Av	%M3 - %GDP	NAICU_GAP	17
18	CU_ANDI	FCI	PC_ALL_ROLL	PC_STAT_ROLL	18
19	% CU > Av	Extra_H	NAICU_GAP	%M3 - %GDP	19
20	Tr_B	MI	MI	Tr_B	20
21	MI	Tr_B	PC_STAT	MI	21
22	NAICU_GAP	PC_STAT	Tr_B	Net_Ext_Dd	22
23	PC_STAT	NAICU_GAP	FCI	FCI	23
24	Energy_GAP	Energy_GAP	Net_Ext_Dd	PC_STAT	24
25	%Cred - %GDP	Net_Ext_Dd	%Cred - %GDP	%Cred - %GDP	25
26	Net_Ext_Dd	%Cred - %GDP	Energy_GAP	Energy_GAP	26
27	HP	HP	HP	HP	27
28	BP	BP	BP	BP	28

Ranking	5 Qtr.	6 Qtr.	7 Qtr.	8 Qtr.	Ranking
1	PC Data	PC Data	PC Data	Cap vs. Dd	1
2	Cap vs. Dd	Cap vs. Dd	Cap vs. Dd	PC Data	2
3	CU_FEDE	CU_ANDI	CU_ANDI	CU_ANDI	3
4	Lics	Lics	Lics	Dd_ANDI	4
5	Ret_Sal	Dd_ANDI	CU_FEDE	PC All	5
6	Dd_ANDI	CU_FEDE	Dd_ANDI	Lics	6
7	PC All	Ret_Sal	Ret_Sal	Ret_Sal	7
8	NAIRU_GAP	PC All	% CU > Av	% CU > Av	8
9	CU_ANDI	% CU > Av	PC All	NAIRU_GAP	9
10	% CU > Av	NAIRU_GAP	NAIRU_GAP	CD_GAP	10
11	CD_GAP	CD_GAP	CD_GAP	PC_ALL_ROLL	11
12	PC_DATA_ROLL	HP_Priors	PC_DATA_ROLL	HP_Priors	12
13	HP_Priors	PC_DATA_ROLL	PC_ALL_ROLL	PC_DATA_ROLL	13
14	PC_ALL_ROLL	PC_ALL_ROLL	NAICU_GAP	NAICU_GAP	14
15	NAICU_GAP	NAICU_GAP	Extra_H	CU_FEDE	15
16	? Occupied	Extra_H	HP_Priors	? Occupied	16
17	Extra_H	? Occupied	? Occupied	%M3 - %GDP	17
18	PC_STAT_ROLL	PC_STAT_ROLL	%M3 - %GDP	PC_STAT_ROLL	18
19	%M3 - %GDP	%M3 - %GDP	PC_STAT_ROLL	Extra_H	19
20	Tr_B	Tr_B	Tr_B	MI	20
21	Net_Ext_Dd	Net_Ext_Dd	MI	Tr_B	21
22	MI	MI	Net_Ext_Dd	Net_Ext_Dd	22
23	FCI	PC_STAT	PC_STAT	PC_STAT	23
24	PC_STAT	FCI	FCI	FCI	24
25	%Cred - %GDP	Energy_GAP	Energy_GAP	Energy_GAP	25
26	Energy_GAP	%Cred - %GDP	%Cred - %GDP	HP	26
27	HP	HP	HP	%Cred - %GDP	27
28	BP	BP	BP	BP	28