Independent Authority for Fiscal Responsibility

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Quarterly regional GDP flash estimates for the Spanish economy (METCAP model)

Abstract

In this paper we propose a methodology to estimate on a quarterly basis the GDP of the different regions of Spain, providing quarterly profiles for the annual official observed data. In this way, the paper offers a new instrument for short-term monitoring that allows the analysts to quantify the degree of synchronicity among regional business cycles.

Technically, we combine time series models with benchmarking methods to process short-term monthly and quarterly indicators and to estimate quarterly regional GDPs ensuring their temporal and transversal consistency with the National Accounts data. The methodology addresses the issue of non-additivity taking into account explicitly the transversal constraints imposed by the chain-linked volume indexes used by the National Accounts and provides an efficient combination of structural as well as short-term information.

The methodology is illustrated by an application to the Spanish economy, providing real-time quarterly GDP estimates for the period 2000:1 – 2014:4.

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Summary

1 Introduction 3

2 Data 4

2.1 Regional accounts 6
2.2 Short-term regional indicators 7
2.3 Autonomous regional accounts 9

3 Econometric approach 10

3.1 Processing short-term indicators 10
3.2 Design of regional GDP trackers using dynamic factor analysis 11
3.3 Quarterly regional GDPs: initial (unbalanced) estimation 16
3.4 Quarterly regional GDPs: final (balanced) estimation 18

4 Numerical results: Spanish quarterly regional GDPs. 21

5 Conclusions 23

6 References 25

A. Appendix: short-term regional indicators 28

1 Introduction

Monitoring economic conditions at the regional level is an important component in the assessment of the economic state of large and medium size countries as well as for countries with decentralized administrative systems that allow the application of specific economic policies. This is clearly the case for Spain: its medium economic size and its decentralized fiscal system are good reasons to consider explicitly the regional dimension in the evaluation of its global economic conditions and to do it in a timely manner.

In addition, fiscal monitoring and forecasting assessment at the regional level is a key mandate for the Independent Authority for Fiscal Responsibility (Autoridad Independiente de Responsabilidad Fiscal, AIReF) and this is why we propose in this paper the use of a modular and transparent system to ascertain the economic conditions of the Spanish economy at the regional level. In this way, for instance, AIReF can evaluate the degree of homogeneity of the short-term economic conditions at the regional level or estimate its own measures of cyclical and structural fiscal conditions for each region.

The design of the system incorporates the available statistical sources of information at the structural level as well as at the short-term level, satisfying their consistency by means of benchmarking techniques (temporal disaggregation and balancing). At the same time, the system is symmetric in the use of the regional information ensuring, that all the regions are considered in the same way.

In this paper we propose a methodology to obtain quarterly estimates of the Gross Domestic Product (GDP) for all the Spanish regions, derived in a consistent way with the official available data provided by the National Accounts, both Regional Accounts (RA) and Quarterly National Accounts (QNA). In this way, early (or flash) estimates of quarterly GDP at the regional level can be released at the same time as the national GDP. Finally, the methodology ensures that transversal consistency is compliant with the chain-linking procedures, circumventing its non-additive features in the balancing step.

The methodology has three main stages:

1. Processing of the high frequency indicators available at the regional level and estimation, for each region, of a GDP tracker that combines the available short term information using dynamic factor analysis.
2. Temporal disaggregation and interpolation of annual regional GDPs using the corresponding GDP trackers estimated in step 1.
3. Balancing of these initial quarterly estimates in order to ensure transversal consistency with the national quarterly GDP, preserving at the same time the temporal consistency achieved in the previous stage.

Our paper relies heavily on Cuevas et al. (2011, 2015), modifying their work in two critical issues. First, we introduce dynamic factor models to estimate the high-frequency (quarterly) regional GDP trackers instead of static factor models. In this way, we enrich the dynamic specification of the models and we obtain a measure of the uncertainty around the GDP tracker. Second, we expand their set of indicators to take into account the financial conditions at the regional level.

The paper is organized as follows. The second section describes the available statistical sources of information used by the system. The third section is devoted to the modeling approach, going into detail of its main steps. A complete and in depth application of the methodology using Spanish data appears in section four. The paper ends presenting the main conclusions and future lines of research.

2 Data

The model requires as input three elements that vary according to their sampling frequency (annual or quarterly), their spatial coverage (regional or national) and their method of compilation (National Accounts or short-term indicators).

The variables of the system are: regional GDPs (*y*), national GDP (*z*) and regional short-term indicators in original or raw[1] form (*xr*). Upper-case letters refer to annual variables while lower-case letters refer to quarterly variables. Let *T=1..N* be the annual (low-frequency) index, *s=1..4* the seasonal index within a natural year and *j=1..M* the regional (cross-section) index. In addition, for each *s*, *T* and *j* we observe *k* indicators, indexed by *i*.

Hence, $Y=\{Y_{T,j}: T=1..N; j=1..M\}$ is a *NxM* matrix comprising the annual regional GDPs that play the role of temporal benchmarks of the system. Aggregation of the regional GDPs generates the GDP at the national level[2].

Variable *z* is a *nx1* vector comprising the observed quarterly GDP provided by the QNA, being $n \geq 4N$ the number of available quarterly observations. This figure is available more timely than the regional data and shares with them the corresponding annual GDP volume index[3]:

[1] $$Z_T = \frac{1}{4}\sum_{s=1}^{4} z_{s,T}$$

Finally, *xr* is an *nxkxM* matrix comprising the observed raw quarterly indicators that operate as high-frequency proxies for the regional aggregates *Y*. As will be explained later, we work with the seasonally and calendar adjusted indicators (*x*) instead of the raw indicators (*xr*) and we combine them to derive a quarterly GDP tracker for each region.

Only the indicators *x* are observed at the three dimensions of the system: *T* (annual index), *s* (seasonal index) and *j* (regional index). Therefore, they provide the interpolation basis (formally, once the GDP tracker has been constructed) for *Y* (across the quarterly

[1] That is, incorporating seasonal and calendar effects.

[2] Again, aggregation is performed according to the chain-linking methodology.

[3] For example, taking 2014 as a reference, the QNA released its first estimate of 2014:Q4 on February, 26th, 2015 while the RA released its first estimate of 2014 on March, 27th, 2015. Both estimates share the annual figure for 2014 implicitly provided by the QNA by means of temporal aggregation of the four quarters of 2014.

dimension *s*) and *z* (across the regional dimension *j*). In other words, our objective is to estimate *y* using *x* as interpolators and consistently with both *Y* and *z*.

Table 1 resumes the relationship among the inputs of the system (*Y*, *z* and *x*) and the output (*y*) for a simplified case with two regions (*M=2*) and two years (*T=2*). The first year is complete while the second year is incomplete (i.e., the last two quarters are not available for *x* and *z* and the annual figure for *Y* is not available either).

Table 1: Information set

		Region 1			Region 2			Nation
Year	Quarter	x_1	y_1	Y_1	x_2	y_2	Y_2	z
1	1	$x_{1,1,1}$	$y_{1,1,1}$	$Y_{1,1}$	$x_{2,1,1}$	$y_{2,1,1}$	$Y_{2,1}$	$z_{1,1}$
	2	$x_{1,2,1}$	$y_{1,2,1}$		$x_{2,2,1}$	$y_{2,2,1}$		$z_{2,1}$
	3	$x_{1,3,1}$	$y_{1,3,1}$		$x_{2,3,1}$	$y_{2,3,1}$		$z_{3,1}$
	4	$x_{1,4,1}$	$y_{1,4,1}$		$x_{2.4,1}$	$y_{2,4,1}$		$z_{4,1}$
2	1	$x_{1,1,2}$	$y_{1,1,2}$		$x_{2,1,2}$	$y_{2,1,2}$		$z_{1,2}$
	2	$x_{1,2,2}$	$y_{1,2,2}$		$x_{2,2,2}$	$y_{2,2,2}$		$z_{2,2}$
	3							
	4							

Note: bold variables are temporal constraints (Y) or transversal constraints (z).

In this simplified example we want to estimate during the first year the quarterly regional GDPs ($y_{j,s,1}$) consistently with their annual counterparts ($Y_{j,1}$) and satisfying the transversal constraint that links each quarter of the regional GDPs with the national quarterly GDP ($z_{s,1}$). The annual constraints do not apply during the second year since $Y_{j,2}$ are not available. So, the only binding constraint is the transversal constraint.

2.1 Regional accounts

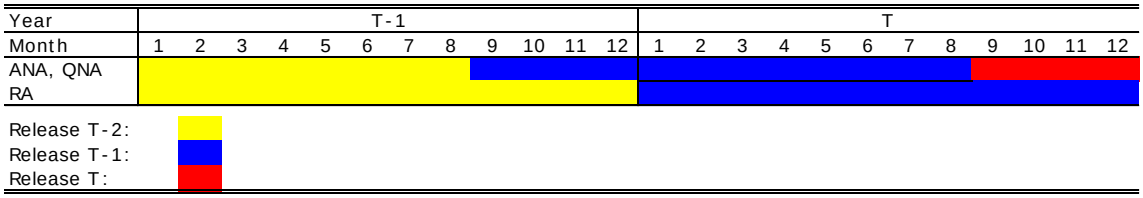
Regional Accounts (RA) have an annual frequency and define the temporal benchmark that our quarterly GDP estimates have to match. They define a homogeneous and consistent measure across the regional dimension, including nominal and real valuation of economic aggregates, coherence with the national data and fulfillment of the principles contained in the European System of National Accounts.

Apart from its annual frequency, another feature of the RA is its delay with respect to the QNA. Our methodology solves this drawback, providing quarterly regional GDPs consistent with the national quarterly GDP, taking into account the chain-linking procedures that underlie its compilation. Note that the same principles of volume estimation using chain-linked indices have been used in our analysis and that we have applied the same procedures of seasonal and calendar adjustment used by the QNA.

Structural consistency is also ensured since the quarterly regional GDPs are consistent with their annual Regional Accounts counterparts. The fact that both QNA and RA share the same National Accounts (NA) framework[4] provides the base for the consistency obtained in our analysis. In this way, we can use the quarterly regional estimates to derive structural measures at the regional level.

An additional drawback of the RA is their lack of synchronicity with the Annual Accounts during four months. Annual and QNA are revised each August but RA incorporate those revisions in December. The following figure illustrates the case:

Figure 1: Internal synchronicity of the National Accounts



2.2 Short-term regional indicators

This subsection details the indicators that have been selected for model estimation. The selection process was carried out under the premise that the indicators should be available timely and should provide a meaningful economic measure for the regional

[4] In particular, the 2010 European System on National Accounts (ESA-2010).

economies. An additional requirement is that they should be homogeneously compiled for all the regions.

The criteria for the choice of these variables is to consider the regional counterpart of all the indicators used in the compilation of the Quarterly National Accounts, see Álvarez (1989), Martínez and Melis (1989), INE (1993) and Álvarez (2005). To fulfill this goal, we have prepared a set of monthly regional indicators that provides a fairly comprehensive basis for analyzing and monitoring GDP at the regional level. This set offers a high-frequency approximation to the behavior of the main macroeconomic aggregates, both real and financial.

The final selection of the indicators has been performed using a stepwise procedure[5]. The starting point is a minimal set of indicators for each region that represent the main economic sectors: index of industrial production (IPI), services sector activity index (IAS), new building permits: total area to build in housing (VIS) for the industrial, construction and services sector, respectively. In addition, we have included a measure of aggregate employment (registered workers at the social security system, AFI) and an indicator of the financial conditions (total Credit to resident sectors, CRE).

The remaining indicators listed in the Appendix A have been ranked according to their correlations with the corresponding regional GDP growth. In order to consider symmetrically all the regions, the average correlation defines the ranking.

The stepwise procedure adds the more correlated indicator to the dynamic factor model to estimate new regional GDP trackers. If the correlation of the new regional GDP tracker increases, the indicator is added to the model. Otherwise, the indicator is dropped from the list. The procedure is repeated until the full list is exhausted.

[5] See the Appendix A for a detailed description of all the indicators that have

The selected indicators are:

- AFI: Social security system: registered workers.
- IPI: Index of Industrial Production.
- PER: Overnight stays in hotel establishments.
- IAS: Services sector activity indicator.
- ICM: Retail sales index.
- IMP: Imports of goods.
- VIS: New building permits: total area to build in housing.
- HIP: Mortgages on housing.
- CRE: Total Credit: public administration and other resident sectors.
- DEP: Deposits: public administration and other resident sectors.
- GAS: consumption of petroleum products.

The short-term indicators, in order to be consistent with the QNA data, have been seasonally and calendar adjusted. Quarterly indicators have been temporally disaggregated to the monthly frequency by means of the quadratic optimization procedure of Boot et al. (1965).

2.3 Autonomous regional accounts

Several Spanish regions compile their own GDP at the quarterly frequency. Although all of them share the general principles contained in the European System of National Accounts they are not homogeneous in their methodology, selection of sources, operational procedures and time coverage. This lack of homogeneity precludes their use as an additional source of information in the model.

3 Econometric approach

In this section we present the main steps of the proposed methodology. The modeling approach consists of three basic steps: (i) seasonal adjustment of regional short-term raw indicators and construction of GDP tracker for each region by means of factor analysis, (ii) initial quarterly estimates of regional GDP provided by benchmarking and (iii) enforcement of the transversal constraint that links the regional quarterly GDPs with their national counterpart.

This aggregation constraint must be consistent with the chain-linking procedure used to compile quarterly GDP at the national level, dealing with the non-additivity issue in an appropriate way. We now turn to examine the three stages in more detail but, to simplify the exposition, we first present the required information set.

3.1 Processing short-term indicators

Typically, short-term regional economic indicators are compiled in raw form by the statistical agencies. However, the volume GDP used for short-term monitoring at the national level is calculated in two ways: using raw indicators or using seasonal and calendar adjusted indicators. Since seasonal and calendar effects could be quite different between indicators and the macroeconomic aggregates, the second procedure for the calculation of the GDP seems more reliable. Usually these GDP figures are referred as seasonal and calendar adjusted.

In order to ensure the homogeneity between both sources of information, regional raw indicators and seasonally adjusted quarterly national GDP, we apply an ARIMA model-based correction that filters out the raw data from seasonal and calendar effects, if they are present. The procedure has been implemented using the TRAMO-SEATS program, see Gómez and Maravall (1995) and Caporello and Maravall (2004). Formally:

[2] $$x_{i,j,s,T} = V(B,F;\theta_{i,j}) \, x \, r_{i,j,s,T}$$

where $xr_{i,j,s,T}$ is the raw short-term indicator[6]; $V()$ is the Wiener-Kolmogorov filter symmetrically defined on the backward and forward operators B and F and $\theta_{i,j}$ are the parameters of the filter derived consistently with those of the ARIMA model for $xr_{i,j,s,T}$, see Gómez and Maravall (1998a, 1998b) for a detailed exposition of the model-based approach used by TRAMO-SEATS.

If the indicators are available at the monthly frequency, seasonal adjustment is performed on the monthly series. The resulting series are temporally aggregated to the quarterly frequency. We have used TRAMO-SEATS because it is the method used by the Spanish National Statistical Institute (NSI) to adjust GDP from seasonal effects.

In practice, several short-term economic indicators are used to monitor and estimate regional GDPs. These indicators are individually processed according to [2] and then linearly combined, producing a composite indicator that will be used as the high-frequency proxy for regional GDPs. As we shall explain in the third section, we use dynamic factor analysis to estimate a GDP tracker indicator for each region because it provides an objective and simple way to combine the available indicators.

3.2 Design of regional GDP trackers using dynamic factor analysis

GDP tracker for each region are estimated by means of a dynamic one-factor model that captures in a parsimonious way the dynamic interactions of a set of monthly economic indicators. The common factor of the system is estimated by means of the Kalman filter, after casting the factor model in state space form. On the basis of this factor we design a GDP tracker that is related to annual RA data through benchmarking techniques (temporal disaggregation). The entire procedure has been adapted to operate with unbalanced data panels.

Dynamic factor analysis is based on the assumption that a small number of latent variables generate the observed time series trough a stochastically perturbed linear structure. Thus, the pattern of observed co-movements is decomposed into two parts:

[6] If calendar effects (e.g., Easter effect and trading day effect) are present, a preliminary correction is also performed. Without loss of generality, we will continue to call the possibly calendar-corrected data as raw data.

communality (variation due to a small number of common factors) and idiosyncratic effects (specific elements of each series, uncorrelated along the cross-section dimension).

In this paper we assume that the observed, stationary growth signals of *k* monthly indicators are generated by a factor model:

[3] $$z_{i,t} = \lambda_i f_t + u_{i,t}$$

Being:

- *t=1..n*, quarterly time index *t=1..sT*.
- $z_{i,t}=(1-B)ln(x_{i,t})$: i-th indicator growth signal at time *t*.
- λ_i: i-th indicator loading on common factor.
- f_t: common factor at time *t*.
- $u_{i,t}$: specific or idiosyncratic component of i-th indicator at time *t*.

The loadings λ_i measure the sensitivity of the growth signal of each indicator for changes in the factor.

Equation [3] only considers static (i.e., contemporaneous) interactions among the observed indicators trough its common dependence on a latent factor. The model should be expanded in order to adapt it to a time series framework, thereby adding a dynamic specification for the common factor and the idiosyncratic elements.

A second-order autoregression, AR(2), provides a sufficiently general representation for the common factor:

[4] $$(1 - \phi_1 B - \phi_2 B^2) f_t = a_t$$
$$a_t \sim iid\ N(0,1)$$

In [4] *B* is the backward operator $Bf_t=f_{t-1}$ and the variance of the innovation has been normalized. Depending on the characteristic roots of $\phi_2(B)$ the model may exhibit a wide variety of dynamic behaviors.

We consider an AR(1) specification for the dynamics of the specific elements, allowing for some degree of persistence:

[5] $$(1 - \psi_i B)\, u_{i,t} = b_{i,t} \qquad |\psi_i| < 1$$
$$b_{i,t} \sim iid\, N(0, v_i)$$

Finally, we assume that all the innovations of the system are orthogonal:

[6] $$E(a_t b_{i,t-h}) = 0 \qquad \forall i, t, h$$
$$E(b_{i,t} b_{j,t-h}) = 0 \qquad \forall i, j, t, h$$

Model [3]-[6] attempts to represent the static as well as the dynamic features of the data. We estimate the common and idiosyncratic factors using the Kalman filter, after a suitable reparameterization of the model in state-space form. The reparameterization requires the introduction of a state vector that encompasses all the required information needed to project future paths of the observed variables from their past realizations. In our case, this vector is:

[7] $$\eta_t = [f_t \quad f_{t-1} \quad u_{1,t} \quad \cdots \quad u_{k,t}]'$$

The corresponding measurement equation is:

[8] $$Z_t = [L \quad 0_{kx1} \quad I_k]'\, \eta_t = H \eta_t$$

L={λ_i i=1..k} represents the loading matrix. This equation allows us to derive the observed indicators from the (unobservable) state vector.

The transition equation completes the system and characterizes its dynamics:

[9] $$\eta_t = G\eta_{t-1} + V_t$$

G is a square matrix with dimension *k+2*:

[10] $$G = \begin{bmatrix} \phi_1 & \phi_2 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & \psi_1 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \psi_k \end{bmatrix}$$

The innovations vector V_t is:

[11] $$V_t = [a_t \quad 0 \quad b_{1,t} \quad \cdots \quad b_{k,t}]'$$

V_t evolves as a Gaussian white noise with diagonal variance-covariance matrix as follows:

[12] $$Q = E[V_t V_t'] = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & v_1 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & v_k \end{bmatrix}$$

We assume that the time index *t* goes from 1 to *T*. The application of the Kalman filter requires $\Theta = [H, G, Q]$ to be known. Since the model is not small-scale, full-system maximum likelihood estimates for Θ are difficult to implement. Our solution was to derive them from the static version of the model, using the transversal panel.

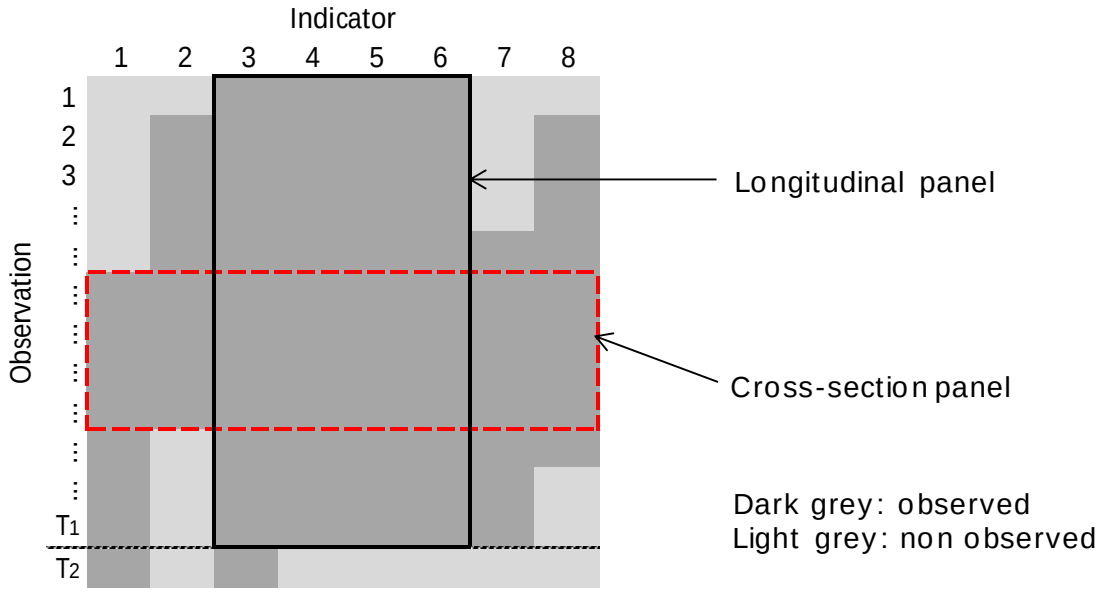
Once we have estimated the common factor via Kalman filter, we can obtain a level time series $F_{t|t}$ through the integration process described in Kim and Nelson (1999). Formally:

[13] $$F_{t|t} = F_{t|t-1} + f_{t|t}$$

The recursion [13] starts from a given initial condition, i.e. $F_{1|0} = 100$.

One of the major operational problems faced while analyzing multiple time series is the incomplete nature of the available information. In general, the availability of different indicators is not homogeneous, which leads to the generation of a non-overlapping sample.

Figure 2: Unbalanced panel data



One way to deal with unbalanced panels consists in working only with complete panels, in the time dimension or in the cross-section dimension. As shown in Figure 2.3, in the first case we may discard a large number of the relevant indicators, with likely adverse effects on factor estimation accuracy and forecasting performance. In the second case, the number of observations may be too small when some series have a short span, making the forecasting or backasting horizon too long.

Given these drawbacks we propose a way to utilize all available information, both on the cross-section dimension and on the time dimension. The method, which is partially based on Stock and Watson (2002) and Giannone et al. (2006), relies on an iterative process with the following steps:

1. Estimation of a static factor model by principal components using the longitudinal panel data.

2. The indicators that have been excluded from the longitudinal panel are individually regressed (by ordinary least squares, OLS) on the common factor.

The estimated parameters are then used to calculate the missing data in these series from *t=1* to $t=T_1$.

3. The parameters $\Theta = [H, G, Q]$ required by the Kalman filter are estimated using the transversal panel, ensuring a symmetric treatment of the available information.

3.3 Quarterly regional GDPs: initial (unbalanced) estimation

Preliminary estimates of quarterly GDP at the regional level are compiled using benchmarking techniques, see Di Fonzo (1987, 2002) and Proietti (2006) for an in-depth exposition. These techniques play an important role in the compilation practices of Quarterly National Accounts around the world, see Eurostat (1998) and Bloem et al. (2001).

We have considered several benchmarking procedures to derive the preliminary GDP estimates: Chow-Lin (1971), Fernández (1981), Santos Silva-Cardoso (2001) and Proietti (2006). All of them hinge around a dynamic linear model that links the (observable) high-frequency indicator (GDP tracker in our case, estimated using dynamic factor modeling) with the (unobservable) regional GDP[7]:

[14] $$y_t = \phi y_{t-1} + \beta_0 F_t + \beta_1 F_{t-1} + u_t$$

The innovation *u* follows an AR(1) process:

[15] $$u_t = \rho u_{t-1} + a_t$$

Finally, the random shock that drives the innovation *u* is Gaussian white noise process:

[16] $$a_t \sim iidN(0, v_a)$$

The model includes a temporal constraint that makes *y* quantitatively consistent with its annual counterpart *Y*:

[7] To keep the notation simple we have omitted the regional index *j*.

[17] $$Y = Cy$$

C is the temporal aggregation-extrapolation matrix defined as:

[18] $$C = (I_N \otimes c \mid O_{N,n-sN})$$

Where *N* is the number of low-frequency observations, $\otimes$ stands for the Kronecker product, *c* is a row vector of size *s* which defines the type of temporal aggregation and *s* is the number of high frequency data points for each low frequency data point. If *c=[1,1,...,1]* we would be in the case of the temporal aggregation of a flow, if *c= [1/s,1/s,...,1/s]* in the case of the average of an index and, if *c=[0,0,...,1]*, an interpolation would be obtained. In our case, *s=4*.

Extrapolation arises when *n>sN*. In this case, the problem can easily be solved by simply extending the temporal aggregation matrix by considering new columns of zeroes which do not distort the temporal aggregation relationship and that do not pose any difficulty to the inclusion of the last *n-sN* data points of the indicators in the estimation process of *y*.

The different benchmarking methods depend on the values of the parameters in [14] and [15] according to table 2:

Table 2: Benchmarking methods

	Parameter		
Method	ϕ	β_1	ρ
Chow-Lin	0	0	(0,1)
Fernández	0	0	1
Santos Silva-Cardoso	(0,1)	0	0
Proietti	(0,1)	≠0	0

The methods of Chow-Lin and Fernández places the dynamics in the innovation, that may follows a stationary AR(1) process (Chow-Lin) or a non-stationary I(1), random walk process (Fernández)[8]. On the other hand, the methods of Santos Silva-Cardoso and

[8] Litterman (1983) proposes a methodology affine to those of Chow-Lin and Fernández. However, the empirical and Monte Carlo evidence show that its performance is sometimes disappointing. This fact is due

Proietti places the dynamics in the variables *y* and *x*, treating the innovation as a purely random shock[9].

The estimation of the parameters and the unobserved time series *y* is performed by maximizing the implied log-likelihood profile of the low-frequency model[10]. This optimization is performed by means of a grid search on the stationary domain of ϕ or ρ, and pinning down the values of β and σ that maximizes the log-likelihood function conditioned on the selected value for ϕ or ρ, see Bournay and Laroque (1979) for an in-depth exposition. The computations have been carried on using the functions written in Matlab by Abad and Quilis (2005).

3.4 Quarterly regional GDPs: final (balanced) estimation

The estimates derived in the previous step do not verify the transversal constraint that should relate them to the national quarterly GDP, satisfying the same type of relationship that links annual regional GDPs and annual national GDP. We solve the problem applying a multivariate balancing procedure, in particular a multivariate extension of the Denton (1971) method. This extension can be expressed in matrix form, as in Di Fonzo (1990) and Di Fonzo and Marini (2003), as well as in state space form, see Proietti (2011). In this paper we have adopted the former approach, using the functions written in Matlab by Abad and Quilis (2005).

This balancing method depends on the formulation of additive constraints. However, volume indexes compiled according to the chain-linking methodology are non-additive, see Bloem et al. (2001) and Abad et al. (2007). Fortunately, we can transform the chain-linked measures in order to write them in an additive form and then use the powerful machinery of balancing procedures to ensure transversal and temporal consistency. Finally, we can express the results in the initial chain-linked format by reversing the transformation.

to the flatness of the implied likelihood profile and, therefore, the corresponding observational equivalence in a wide range of values for its dynamical parameter, see Proietti (2006).

[9] Gregoir (1994) and Salazar et al. (1994) also propose methods in which the dynamics of *y* and *x* play an explicit role.

[10] The low-frequency model incorporates the temporal aggregation constraints [17] and [18].

The constraint that links regional and national quarterly volume GDP is:

[19] $$z_{t,T} = \left(\sum_{j} W_{j,T-1} \frac{y_{j,s,T}}{Y_{j,T-1}} \right) Z_{T-1}$$

Where $z_{t,T}$ is the national quarterly volume GDP, $W_{j,T-1}$ is the weight of region j in year $T-1$ and $y_{j,s,T}$ is the quarterly volume GDP of the j-th region[11]. Finally, Z_T and $Y_{j,T}$ are the annual counterparts $z_{t,T}$ of and $y_{j,s,T}$.

After some algebraic manipulations, we can express the constraint in additive form:

[20] $$\underbrace{\frac{z_{t,T}}{Z_{T-1}}}_{r_{t,T}} = \sum_{j} \underbrace{W_{j,T-1} \frac{y_{j,s,T}}{Y_{j,T-1}}}_{wr_{j,t,T}} = \sum_{j} wr_{j,s,T}$$

In [20] the relationship between the national ratio $r_{t,T}$ and the weighted regional ratios $wr_{j,s,T}$ is additive.

Plugging the initial estimates derived according to [3]-[7] into [9] we obtain the preliminary, unbalanced estimates:

[21] $$wr^{*}_{j,s,T} = W_{j,T-1} \frac{\hat{y}_{j,s,T}}{Y_{j,T-1}}$$

The balanced and temporally consistent time series $wr^{**}_{j,t,T}$ are the output from the following constrained quadratic optimization program:

[11] Weights are computed using GDPs valued at current prices, see Abad et al. (2007) for a complete derivation.

[22] $$\underset{wr^{*}}{MIN} \quad (wr^{**} - wr^{*})'D'D(wr^{**} - wr^{*}) \qquad s.t. \quad Hwr^{**} = R_e$$

Being:

$$H = \begin{bmatrix} 1_M' \otimes I_n \\ I_M \otimes C \end{bmatrix} \quad \text{and} \quad R_e = \begin{bmatrix} z \\ WR \end{bmatrix}$$

Where 1_M is a column vector of ones and *WR* is the annual counterpart of the weighted regional ratios written in matrix form.

In the program [22] the objective function reflects the volatility of the discrepancies between the quarter-to-quarter growth rates of the balanced series and those of the unbalanced ones. After some mathematical manipulation, an explicit expression can be derived:

[23] $$wr^{**} = wr^{*} + (D'D)^{-1}H'\left[H(D'D)^{-1}H'\right]^{-1}(R_e - Hwr^{*})$$

The interpretation of equation [23] is straightforward: the quarterly balanced series are the result of adding up a correction factor to the unbalanced series. This correction factor originates from the distribution of the discrepancy between the preliminary unbalanced estimates and the constraint series R_e.

Once we have obtained the consistent weighted ratios, we can reverse the transformation [20] to derive the final estimates of the quarterly regional GDP in volume terms:

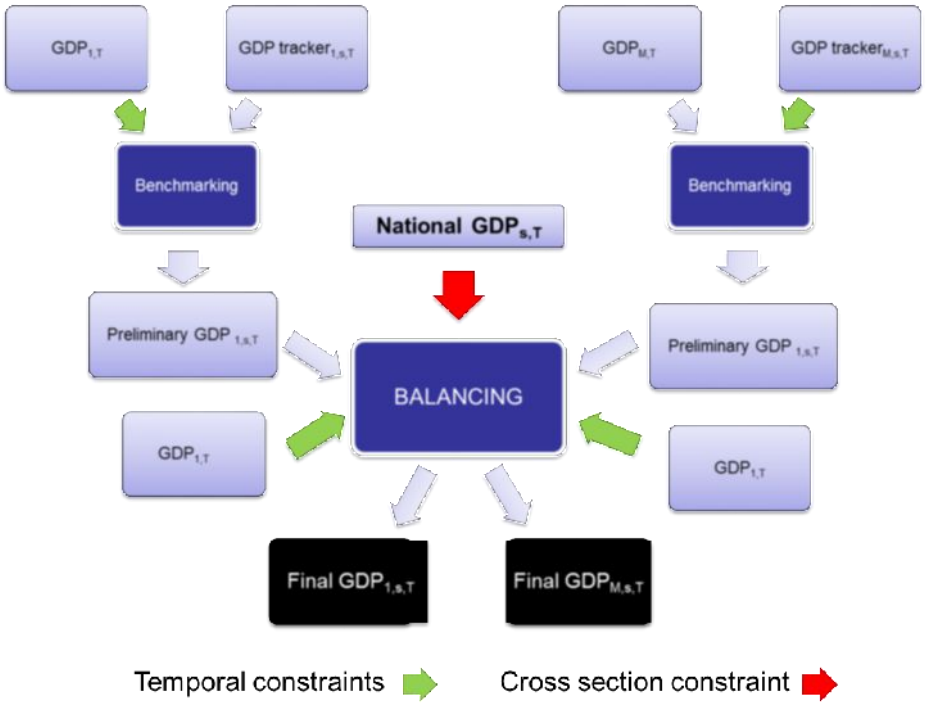
[24] $$y^{**}_{j,s,T} = wr^{**}_{j,s,T}\frac{Y_{j,T-1}}{W_{j,T-1}}$$

In this way, the estimates of quarterly GDP derived in the previous equation are quantitatively consistent in their time dimension (taking as benchmark their annual regional counterparts) and in their cross-section dimension (generating the GDP provided by the QNA by regional aggregation). We should also emphasize that the consistency extends to the methodological dimension too, since the chain-linking procedures in current use by the National Accounts have been properly taken into

account. Finally, using time series methods to project the basic short-term indicators we can derive nowcasts (or flash estimates) of regional quarterly GDP in a timely way.

As a summary, the figure 3 presents a picture of the complete procedure. The diagram emphasizes the binding constraints and the homogeneous processing of information at the regional level. Note that the box labeled “balancing” embeds the de-chaining and re-chaining steps required to circumvent the non-additive features of the chain-linked volume indexes.

Figure 3: Schedule of steps 2 (Benchmarking) and 3 (Balancing)



*Note: In **bold** national variables. Seasonal quarterly index s goes from 1 to 4; annual index T goes from 1 to N and regional index j goes from 1 to M.*

4 Numerical results: Spanish quarterly regional GDPs.

We have performed a complete exercise using the data above mentioned to get the quarterly GDP by region for the period 2000:Q1 – 2014:Q4.

As mentioned previously, to combine in an efficient and operative way the information contained in the individual monthly indicators, we have calculated a synthetic indicator for each region. In order to have an idea of the correlation between the individual indicators and the estimated synthetic indicator (common factor) table 3 shows the loading vectors, estimated by means of principal components factor analysis. The estimation has been performed on the first differences of the log-transformed indicators.

Table 3: Regional GDP trackers: loading structure

	AFI	IMP	IPI	VIS	PER	CRE	HIP	DEP	GAS	ICM	IAS
Andalucía (AND)	0.67	0.03	0.45	0.18	0.28	0.65	0.29	0.57	0.34	0.62	0.65
Aragón (ARA)	0.50	0.31	0.52	0.02	0.16	0.41	0.01	0.23	0.53	0.74	0.73
Asturias (AST)	0.58	0.13	0.29	0.33	0.32	0.46	0.16	0.32	0.44	0.74	0.72
Baleares (BAL)	0.35	0.02	0.45	0.22	0.28	0.18	0.06	0.22	0.52	0.82	0.82
Canarias (CAN)	0.72	0.01	0.34	0.22	0.34	0.47	0.07	0.39	0.10	0.82	0.73
Cantabria (CANT)	0.62	0.01	0.23	0.10	0.23	0.66	0.10	0.53	0.16	0.69	0.72
Castilla León (CYL)	0.64	0.01	0.31	0.22	0.30	0.49	0.15	0.31	0.32	0.74	0.67
Castilla La Mancha (CLM)	0.39	0.12	0.52	0.22	0.33	0.53	0.29	0.47	0.52	0.69	0.63
Cataluña (CAT)	0.61	0.31	0.63	0.36	0.01	0.40	0.37	0.30	0.45	0.75	0.76
Comunitat Valenciana (VAL)	0.72	0.10	0.61	0.10	0.32	0.47	0.30	0.40	0.45	0.76	0.78
Extremadura (EXT)	0.66	0.14	0.01	0.07	0.10	0.65	0.18	0.61	0.47	0.64	0.56
Galicia (GAL)	0.62	0.28	0.28	0.21	0.42	0.48	0.16	0.28	0.28	0.68	0.63
Madrid (MAD)	0.68	0.22	0.44	0.27	0.28	0.52	0.10	0.39	0.34	0.66	0.60
Murcia (MUR)	0.67	0.07	0.42	0.01	0.01	0.65	0.22	0.69	0.34	0.68	0.57
Navarra (NAV)	0.47	0.15	0.45	0.20	0.31	0.42	0.01	0.26	0.41	0.69	0.77
País Vasco (PV)	0.54	0.34	0.50	0.01	0.13	0.47	0.21	0.25	0.33	0.67	0.71
La Rioja (RIO)	0.43	0.33	0.28	0.01	0.13	0.44	0.27	0.24	0.33	0.67	0.77

We must emphasize the relevance of the IAS (Turnover index for the sector services) and the ICM (Retail sales index), no strange thing because services typically represent about 60% of GDP, followed by MAT (Car registrations), IPI (Industrial production index) and AFI (Registered workers in Social Security system).

As second step, the corresponding monthly regional synthetic indicators (GDP tracker) are temporally aggregated to the quarterly frequency and a temporal disaggregation technique is implemented in order to get the initial quarterly GDP estimates. Following the results obtained in Cuevas et al. (2011, 2015), the Fernandez[12] method is chosen

[12] Regarding the distinction between Fernández or Chow-Lin method, the results of the exercise show an innovational parameter with Chow-Lin close to 1 (approximately 0.98-0.99 in most cases), so under this situation both methods are practically equivalent.

because it ensures a stronger link to the evolution of the indicator, and also is one of the currently suggested methods for the compilation of the Spanish QNA, see Quilis (2005).

The third step is the balancing procedure, ensuring transversal consistency with national quarterly GDP and preserving temporal consistency with the annual regional GDP.

Once the process is complete and in order to illustrate the results, table 4 presents the evolution of the estimated quarter-on-quarter rates of growth in the quarterly frequency:

Table 4: Dating recession in quarterly GDP (q-o-q rates of growth)

	2008				2009				2010				2011				2012				2013				2014			
	T I	T II	T III	T IV	T I	T II	T III	T IV	T I	T II	T III	T IV	T I	T II	T III	T IV	T I	T II	T III	T IV	T I	T II	T III	T IV	T I	T II	T III	T IV
Spain	0.5	0.1	-0.8	-1.0	-1.6	-1.0	-0.3	-0.1	0.3	0.2	0.0	0.0	-0.1	-0.3	-0.5	-0.4	-0.6	-0.6	-0.5	-0.8	-0.3	-0.1	0.1	0.3	0.3	0.5	0.5	0.6
Andalucía	0.1	0.0	-0.8	-0.9	-1.2	-1.1	-0.7	-0.6	-0.2	-0.2	-0.1	-0.1	0.2	-0.4	-0.6	-0.4	-1.1	-0.8	-0.7	-0.6	-0.3	0.2	0.0	0.4	0.4	0.2	0.5	0.6
Aragón	0.7	0.1	-0.5	-2.3	-1.4	-0.3	-0.2	0.4	0.4	-0.2	0.2	0.6	-0.5	-0.4	-0.8	-1.2	-0.9	-1.4	-0.5	-1.0	0.1	0.3	0.5	0.3	0.2	0.8	0.3	0.7
Asturias	0.7	0.0	-0.8	-1.3	-2.4	-1.1	-0.6	0.0	0.7	0.0	0.2	0.2	-0.2	-0.3	-0.7	-0.9	-0.9	-1.1	-0.8	-1.4	-0.6	-0.4	0.0	0.0	0.2	0.6	0.4	0.3
Baleares	0.9	0.0	-1.2	-0.9	-1.5	-1.3	-0.5	-0.2	-0.1	-0.3	0.0	0.0	-0.2	0.6	0.3	-0.3	0.2	-0.7	-0.2	-0.6	0.0	0.1	0.1	0.2	0.3	1.0	0.7	1.1
Canarias	0.0	0.1	-1.3	-1.4	-2.0	-1.0	-0.2	0.0	0.6	0.3	0.6	-0.4	0.1	-0.4	-0.4	-0.4	-0.3	-0.3	-0.7	-0.3	-0.2	0.1	0.3	0.6	0.6	0.6	0.7	0.8
Cantabria	0.4	0.3	-0.9	-1.0	-1.5	-1.1	-0.6	-0.1	0.5	0.3	-0.4	-0.4	-0.6	-0.5	-0.5	-0.2	-0.3	-0.4	-0.6	-0.9	-0.9	-0.6	0.1	0.2	0.4	0.3	0.3	0.6
Castilla León	-0.1	-0.3	-0.2	-0.5	-1.4	-0.7	-0.3	0.3	0.4	0.2	0.2	0.3	0.2	0.2	-0.6	-0.7	-0.9	-1.2	-0.6	-0.9	-0.5	-0.2	0.1	0.3	0.3	0.6	0.6	0.4
Castilla La Mancha	1.1	0.1	-0.6	-1.2	-1.4	-0.6	-0.6	-0.5	-0.2	-0.2	0.4	0.1	0.2	-0.3	-1.0	-0.8	-1.6	-1.1	-0.7	-1.1	0.0	0.3	0.4	0.5	0.0	0.3	0.5	0.4
Cataluña	0.4	-0.4	-0.9	-1.1	-1.8	-0.7	0.0	0.2	0.5	0.4	-0.2	-0.1	-0.7	-0.6	-0.5	-0.4	-0.4	-0.6	-0.4	-0.9	-0.2	-0.1	0.3	0.2	0.2	0.6	0.6	0.8
Com. Valenciana	0.7	-0.1	-1.1	-1.6	-2.5	-1.5	-0.2	-0.5	0.2	0.1	-0.2	-0.1	-0.3	-0.6	-0.6	-0.6	-0.8	-1.0	-0.6	-0.6	-0.1	0.1	0.4	0.6	0.2	0.9	0.5	0.8
Extremadura	0.5	0.4	-0.5	-0.5	-1.5	-0.9	-0.6	0.0	0.4	0.3	0.2	0.0	-0.1	-0.4	-0.9	-0.9	-1.1	-0.8	-0.9	-0.5	-0.3	0.0	0.2	0.7	0.5	0.7	0.7	0.4
Galicia	0.9	0.1	-0.7	-0.4	-1.6	-1.2	-0.3	0.3	0.6	0.4	0.1	-0.4	-0.6	-0.4	-1.1	-0.5	-0.3	-0.7	-0.6	-0.6	-0.2	0.0	0.2	0.1	-0.1	0.1	0.4	0.5
Madrid	0.3	0.4	-0.5	-0.5	-0.9	-0.9	-0.3	-0.1	0.1	0.2	0.1	0.2	0.3	0.0	0.0	0.1	-0.1	-0.1	-0.3	-0.6	-0.6	-0.4	-0.3	0.1	0.3	0.5	0.5	0.7
Murcia	1.0	0.4	-0.7	-0.9	-1.9	-1.6	-0.8	-0.4	0.6	0.3	0.3	-0.1	0.0	-0.3	-0.3	-0.6	-0.9	-0.3	-0.3	-0.5	-0.7	-0.1	0.1	0.6	0.9	0.6	0.2	0.5
Navarra	1.0	0.6	-0.8	-1.3	-1.9	-0.7	0.2	0.4	0.6	0.4	0.4	0.7	0.3	-0.1	-0.7	-0.2	-1.1	-0.7	-0.4	-1.5	0.0	0.0	0.6	0.5	0.6	0.5	0.4	0.5
País Vasco	0.6	0.5	-0.5	-1.4	-2.0	-1.2	0.0	0.5	1.0	0.9	0.1	0.0	-0.2	-0.3	-0.6	-0.1	-0.4	-0.6	-0.3	-0.8	-0.6	-0.5	0.0	0.1	0.5	0.4	0.4	0.6
La Rioja	1.0	0.1	-0.8	-1.5	-2.0	-0.8	-0.1	-0.1	1.1	-0.3	-0.1	0.1	-0.4	-0.6	-0.6	-0.3	-1.4	-0.3	-0.3	-1.7	-0.3	0.0	0.4	0.8	0.7	0.8	0.7	0.6

Negative rates
Minimum rate
Positive rates

The table shows how the crisis has affected regions unevenly. For example, we can place the bulk of the recession between the third quarter of 2008 and the fourth quarter of 2009. Most of the regions fell into recession at the same time but not all of them left it out simultaneously. We can see that many regions fall back into recession after the fourth quarter of 2010, but they experience a new recovery after the third quarter of 2013.

5 Conclusions

In this paper we have presented a feasible way to add a regional dimension to the short-term macroeconomic analysis, satisfying the temporal and cross-section constraints imposed by the National Accounts. Our procedure generates results that are comparable across regions, are based on meaningful short-term economic information and may be updated at the same time as the GDP flash national estimates, providing a solid basis for specific regional estimates.

There are several promising lines of research that may widen the scope of the paper. The modeling approach can be easily extended to accommodate several types of extrapolations. For example, the transversal benchmark of the model (the national quarterly GDP) may be an official release made by the National Statistical Institute or a forecast made by an analyst. In the latter case, we can combine these forecasts with the projected path for the underlying short-term quarterly regional indicators to generate the corresponding regional quarterly GDPs. The resulting conditional extrapolations can be used to asses the expected cyclical position of each region with respect to the nation.

Finally, the estimated regional quarterly GDPs can be used to analyze issues related to the synchronicity of the regional business cycles as well as their pattern of co-movements.

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A. Appendix: short-term regional indicators

- AFI: Social security system: registered workers.
  - Units: persons.
  - Source: Labor department (*Ministerio de Empleo y Seguridad Social*).
  - Starting date: 1995.m1.

- IPI: Index of Industrial Production.
  - Units: Index number.
  - Source: National Statistical Institute (*Instituto Nacional de Estadística, INE*).
  - Starting date: 1995.m1.
  - Back-calculation: combining data from 1990 base (1995.m1-2002.m1) and base 2010 base (2002.m1-present), using the oldest period-on-period rates of growth to retropolate the newest base.

- PER: Overnight stays in hotel establishments.
  - Units: Number of overnight stays.
  - Source: National Statistical Institute (*Instituto Nacional de Estadística, INE*).
  - Starting date: 1995.m1.
  - Back-calculation: The series have been homogenized since 1998.m12 by means of univariate intervention analysis in order to correct from the methodological change introduced in 1999.m1.

- IAS: Services sector activity indicator.
  - Units: Index number. Valuation at current prices.
  - Source: National Statistical Institute (*Instituto Nacional de Estadística, INE*).
  - Starting date: 2005.m1.
  - Deflated using the Consumer Price Index (CPI) for services (house renting excluded).

- ICM: Retail sales index.
  - Units: Index number. Valuation at constant prices, gas stations excluded.
  - Source: National Statistical Institute (*Instituto Nacional de Estadística, INE*).
  - Starting date: 2003.m1.
  - Deflated using the Consumer Price Index (CPI) for services (house renting excluded).

- MAT: Car registrations.
  - Units: Registrations.
  - Source: Traffic department (*Dirección General de Tráfico, Ministerio del Interior)*.
  - Starting date: 1995.m1.

- EXP: Exports of goods.
  - Units: Euros, valuation at current prices.
  - Source: External trade statistics, Ministry of Economy and Competitiveness.
  - Starting date: 1995.m1.
  - Deflated using the national exports unit value index.

- IMP: Imports of goods.
  - Units: Euros, valuation at current prices.
  - Source: External trade statistics, Ministry of Economy and Competitiveness.
  - Starting date: 1995.m1.
  - Deflated using the national imports unit value index.

- VIS: New building permits: total area to build in housing.
  - Units: squared meters
  - Source: Ministry of Public Works

- Starting date: 1995.m1.

- HIP: Mortgages on housing.
  - Units: number
  - Source: National Statistical Institute (*Instituto Nacional de Estadística, INE*).
  - Starting date: 1995.m1.
  - Back-calculation: combining data from old base (1995.m1-2003.m1) and new base (2003.m1-present), using the oldest period-on-period rates of growth to retropolate the newest base.

- CRE: Total Credit to resident sectors.
  - Units: Euros, valuation at current prices
  - Source: Bank of Spain
  - Starting date: 1995 Q1
  - Deflated using the Consumer Price Index (CPI)

- DEP: Deposits: public administration and other resident sectors.
  - Units: Euros, valuation at current prices
  - Source: Bank of Spain
  - Starting date: 1995 Q1
  - Deflated using the Consumer Price Index (CPI)

- GAS: consumption of petroleum products.
  - Units: Tons
  - Source: CORES (strategic oil reserves corporation)
  - Starting date: 1995. m1
  - Deflated using the Consumer Price Index (CPI)

The following table shows the correlation of each indicator with the corresponding regional GDP. The correlation is computed at the annual frequency between their rates of growth:

Table A.1: Correlation between indicators and GDP

Annual data, rates of growth

	AFI	EXP	IMP	IPI	VIS	MAT	PER	CRE	HIP	DEP	GAS	ICM	IAS
AND	0.96	-0.09	0.37	0.86	0.70	0.56	0.67	0.83	0.80	0.85	0.81	0.87	0.77
ARA	0.95	0.45	0.57	0.69	0.68	0.45	0.75	0.79	0.75	0.51	0.67	0.90	0.82
AST	0.96	0.43	0.77	0.71	0.56	0.21	0.76	0.76	0.70	0.49	0.42	0.82	0.92
BAL	0.93	0.53	0.20	0.73	0.50	0.30	0.37	0.61	0.45	0.32	0.59	0.74	0.67
CAN	0.93	0.28	0.51	0.76	0.36	0.42	0.25	0.63	0.61	0.59	0.16	0.80	0.88
CNT	0.96	0.39	0.58	0.55	0.48	0.27	0.61	0.81	0.81	0.58	0.55	0.75	0.75
CYL	0.97	-0.08	0.02	0.74	0.70	0.23	0.78	0.80	0.87	0.46	0.90	0.77	0.79
CLM	0.97	-0.12	0.51	0.66	0.63	0.38	0.81	0.83	0.81	0.72	0.53	0.89	0.66
CAT	0.96	0.41	0.76	0.63	0.64	0.36	0.27	0.72	0.70	0.51	0.60	0.86	0.85
CVA	0.96	0.11	0.69	0.72	0.65	0.49	0.66	0.69	0.69	0.72	0.61	0.88	0.76
EXT	0.95	0.01	0.52	0.69	0.71	0.40	0.40	0.78	0.84	0.73	0.79	0.84	0.91
GAL	0.97	0.47	0.57	0.75	0.71	0.29	0.58	0.80	0.69	0.48	0.49	0.75	0.78
MAD	0.96	0.03	0.68	0.81	0.33	0.42	0.41	0.83	0.54	0.70	0.57	0.84	0.77
MUR	0.94	-0.37	0.39	0.83	0.64	0.33	0.60	0.74	0.81	0.82	0.34	0.83	0.73
NAV	0.96	0.28	0.63	0.79	0.53	-0.09	0.46	0.71	0.61	0.53	0.86	0.82	0.92
PVA	0.93	0.61	0.72	0.85	0.61	0.08	0.38	0.76	0.68	0.35	0.22	0.80	0.90
RIO	0.94	0.28	0.26	0.76	0.60	0.25	0.51	0.79	0.66	0.47	0.47	0.81	0.76
Average	0.95	0.21	0.52	0.74	0.59	0.32	0.55	0.76	0.71	0.58	0.56	0.82	0.80

The corresponding box plot depicts a clear image of the correlation structure underlying in the table:
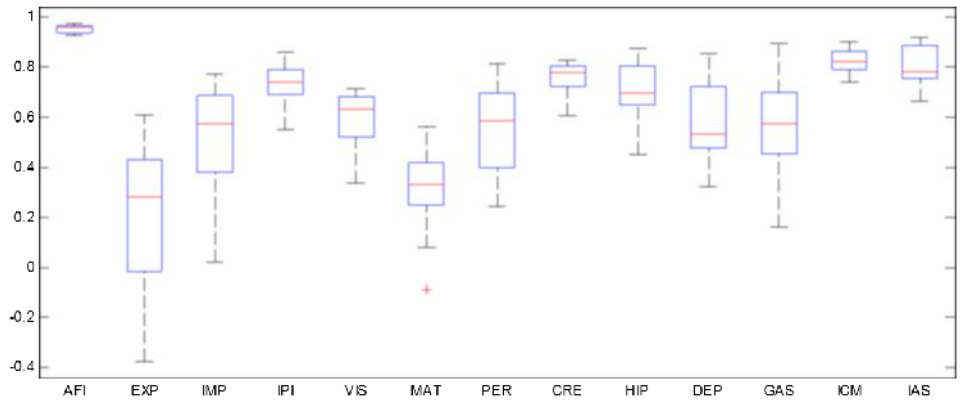
Figure A.1: Box plot of the Correlation between indicators and GDP