

Outline

- Motivation
 - PLS
 - PLSAR
- Quick overview of VAR Models
- Definition for VAR-PLS
- Bootstrap for VAR-PLS
- Conclusions

Motivation

- PLS is a technique that has been proven its impact on many applications such as quality control starting with the *Chemistry*, batch processes, medical images analysis, microarrays, path modeling, classification, discrimination, spatio-temporal PLS models just to mention some, with authors such as McGregor, Nomikos, MacIntosh, V. Esposito Vinz, P. Garthwaite, and so on
- The method can be used in univariate and multivariate data as well
- *It has been shown that gives better prediction even when the standard assumptions are met*
- Phillip Hans Franses (2006) propose a methodology to construct the forecast h steps ahead in an optimal way, through an autoregressive order p : "An Autoregressive Partial Least Square (PLS)" denote as $PLSAR(h, p)$

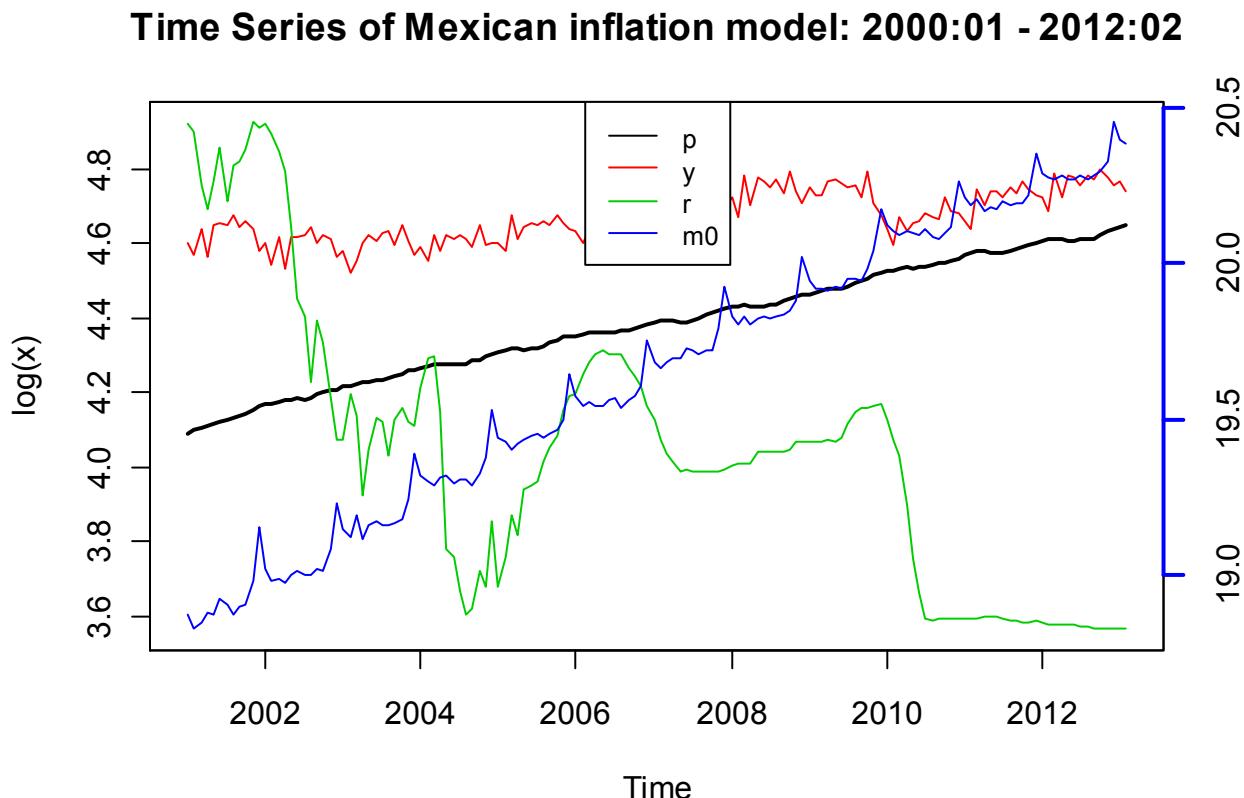
Our case of interest

- Develop a model to predict the Mexican inflation, as precise as possible.
- The model has to consider, as the principal source of the Mexican inflation, the growth and the variation on the monetary condition of the country
- Irrespective of all possible discussions, there seems to be a common understanding into believe that the inflationary process, in the long run, is a purely monetary phenomena
- Here we are not taking the discussion on the existence or not of such relationship but we will show its empirical properties with a model that is tested out of the sample via its error prediction measure.

We work with 4 indexes (we built those) from January 2000 to February 2012:

- **p**: Consumer price index
- **m0**: Monetary base
- **r**: Equilibrium interest rate (28 días)
- **y**: Industrial production index

Relacionar empíricamente la variable de precios, que a su vez es una función de la tasa de inflación (inflación mensual, inflación interanual, acumulada, etc.) con el resto de las variables permitiendo las relaciones multivariadas existentes, generando así un $VAR(p)$ de rango completo y/o un $VECM$ para el caso cointegrado.



Podemos apreciar que la serie de precios lleva una clara tendencia creciente en niveles, el índice monetario presenta una estacionalidad característica en todo el periodo de tiempo, la producción económica con tendencia de menor pronunciación que la serie de precios la cual que a partir del 2010 exhibe cierta recuperación respecto a los niveles observados en la primera mitad del gráfico. La tasa de interés claramente ha tenido un periodo de estabilidad a partir del segundo semestre del 2010.

- We generalized the work proposed by Franses in the following way:
(here we just show some comparative results)
 1. Give a multivariate representation based on the flexibility of the VAR models, model that we will call $VAR - PLS(h, p)$
 2. Extend the model to consider deterministic variables (dummies, trend, etc.) as well as exogenous variables
 3. Bootstrap prediction intervals
 4. Compare the forecast capabilities between a $VAR - PLS(h, p)$ and a forecast VAR model explicitly built for (integral predictor method)
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PLSAR(h,p)

Frances plantea la comparación entre tres formas de hacer pronósticos bajo un AR(p).

- A single model for all horizons , an interative procedure will come on hand (escribir el modelo sin los gorros y con el termino de error y con rho no p)

$$AR(p): y_{T+h} = \hat{\mu} + \hat{p}_1 y_{T+h-1} + \hat{p}_2 y_{T+h-2} + \dots + \hat{p}_p y_{T+h-p} + \hat{\varepsilon}_t$$
- ❖ El modelo $AR(p)$ es la forma clásica de realizar los h pasos hacia adelante cuyos parámetros son estimados generalmente por Mínimos Cuadrados Ordinarios (OLS)
- One model for each horizon, the variance will vary within each horizon (escribir modelo sin los gorros y con el término de error y con rho no p)

$$AR_h(p): y_{t+h} = \hat{\mu} + \hat{p}_{1,h} y_t + \hat{p}_{2,h} y_{t-1} + \dots + \hat{p}_p y_{t-p} + \hat{\varepsilon}_{h,t}$$

The $AR_h(p)$ is an alternative to the $AR(p)$ because

- ❖ OLS minimize the sum of square of $\hat{\varepsilon}_t$ but there is no way to assure it will remain minimum for all the h steps in the future
 - One can count with different models for each step
- ❖ For stationaty time series recall the the forecast of an $AR(p)$ model quickly converge to the unconditional mean (and variance, for the interval predicton error) clearly depending on $h \geq p$

Note: For more details on this type of models see : Pesaran & Pick (2010), Marcellino, Stock & Watson (2004), Carreiro, Kapetorios & Marcellino (2010), Tiao & Xu (1993) among others.

- Something in between: PLSAR, este modelo se encuentra situado entre un $AR(p)$ que pronostica todos los h pasos adelante y diferentes modelos AR para cada horizonte, formuló un modelo para h pronósticos denominado

$$PLSAR(h,p): Y = XB_{PLS} + U$$

- ❖ It is clear that exists adjacent correlation between the time series, and neither one of the above models take them into account. In other words, we know that y_t and y_{t-j} are correlated and so are y_{T+h} and y_{T+h-j} . Therefore we would like to jointly predict $(y_{t+h}, y_{t+h-1}, y_{t+h-2}, \dots, y_{t+1})$ through $(y_t, y_{t-1}, y_{t-2}, \dots, y_{t-p})$. PLS is a techinique very attractive to do so.
- ❖ Frances propose to arrange the information as
 - $(y_t, y_{t-1}, y_{t-2}, \dots, y_{t-p})$ as the predictor X matrix and
 - $(y_{t+h}, y_{t+h-1}, y_{t+h-2}, \dots, y_{t+1})$ as the predicted Y matrix

- Applied the PLS algorithim, to get the latent variables with the relevant information given in X and Y.

His simulations shows that the $PLSAR(h,p)$: is quite competitive with respect to the classical models in the literature.

PLS

- PLS can be tract from different stand points, to us the relationship between its linear expression will be the best one, in order to related with a Vector Autorregresive model

$$Y = XB + U$$

donde Y es $N \times k$, X es una matriz $n \times N$, B es una matriz de $(N+1) \times k$ y U es una matriz de $N \times k$.

The basic procedure maximize the $cov(X\alpha, Y\beta)^2$ under certain restrictions

$$\alpha'(S^*_{xx} + \lambda_x)\alpha = 1 \text{ & } \beta'(S^*_{yy} + \lambda_y)\beta = 1$$

where

$$S^*_{xx} = (1 - \lambda_x)S_{xx} \text{ & } S^*_{yy} = (1 - \lambda_y)S_{yy}$$

- $(X\alpha, Y\beta)$ are linear combinations of the variables that maximize the covariance or actually the square covariance (the sign is not important just the direction)
- S_{xx} y S_{yy} the variance covariance matrices; $\beta'\beta = 1$ & $\alpha'S_{xx}\alpha = 1$

we maximze the the objective function:

$$\mathcal{L} = (\alpha'S_{xy}\beta)^2 - \gamma\{\alpha'(S^*_{xx} + \lambda_x)\alpha - 1\} - \mu\{\beta'(S^*_{yy} + \lambda_y)\beta - 1\}$$

After some algebra we get the **scores** for X y Y , $t = Xw = Ew$ and $u = Yq = Fq$

Normalizing the scores $t = t/\sqrt{t't}$ and after simplifications and more algebra we get the **loadings** for X and Y : $p = E't$ and $q = F't$. Writing in matrix form w, t, p y q we get $R = W(P'W)^{-1}$ that basically recovers the basic information for the estimated parameters

$$Y = XB + U \text{ so } Y(\text{gorro}) = XB_{PLS} \quad \text{where} \quad B_{PLS} = R(T'T)^{-1}T'Y = RQ'$$

Note 1: For a nice introduction see : P.H. Garthwaite (1994). An Interpretation of Partial Least Squares. JASA Vol 89, No 425, pp 122-127 and Agnar Hoskuldsson (1988). PLS Regression Methods. Journal of Chemometrics, Vol 2, pp 221-228.

Note 2: Franses shows that if the B_{PLS} matrix has full rank it implies a different model for each of the columns of Y , and hence a model like (2). In the exceptional case that B_{PLS} has rank 1, then the $AR(p)$ appers.

Vectores Autorregresivos y Mínimos Cuadrados Parciales

A $VAR(p)$ processes is defined as

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + C D_t + u_t \quad (4)$$

A_i : Coefficient Matrices for $i = 1, 2, \dots, p$

ε_t : White noise process with covariance matrix $E[u_t u_t'] = \Sigma_u$

C : Possible deterministic regressor coefficient matrix

D_t : Appropied vector for deterministic variables

It is well know that a $VAR(p)$ model can be written as a $VAR(1)$ in the following way

$$Y_t = A Y_{t-1} + V_t \quad (5)$$

$$Y_t = \begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{bmatrix}$$

$$A = \begin{bmatrix} A_1 & A_2 & \cdots & A_{p-1} & A_p \\ I & 0 & \cdots & 0 & 0 \\ 0 & I & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & I & 0 \end{bmatrix}$$

$$V_t = \begin{bmatrix} u_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

- If the eigenvalues of A are less than one, then the $VAR(p)$ is stable 

- We use the VAR representation to determine the order of the model

The general procedure is quite standard. Order $p = 0, \dots, p_{max}$ and choose the value of p than minimize some criteria. The criteria are usually written as:

$$IC(p) = \ln |\hat{\Sigma}(p)| + C_T \cdot \varphi(K, p)$$

where $\hat{\Sigma}(p) = T^{-1} \sum_{t=1}^T \hat{u}_t' \hat{u}_t$, C_T indexed sequence of the size of the series, T and $\varphi(K, p)$ is a penalty function that involves the order of the $VAR(p)$.

The most common information criterias are: Akaike (AIC), Schwarz-Bayesiano (BIC), Hannan-Quinn (HQ) and Final predicction error (FPE):

$$\begin{aligned} AIC(p) &= |\hat{\Sigma}(p)| + \frac{2}{t} p K^2 \\ BIC(p) &= |\hat{\Sigma}(p)| + \frac{\ln T}{t} p K^2 \\ HQ(p) &= |\hat{\Sigma}(p)| + \frac{2 \ln \ln T}{t} p K^2 \\ FPE(p) &= \left(\frac{T+p^*}{T-p^*} \right)^K \det(\hat{\Sigma}(p)) \end{aligned}$$

- The AIC asymptotically overestimate the order of the model with a positive probability whereas BIC and HQ are consisten estimator of the order if, the real value of is less than or equal than p_{max}

Notemos que al igual que el caso univariado, podemos con (4) pronosticar recursivamente de la siguiente manera:

$$y_{T+h \setminus T} = A_1 y_{T+h-1} + \cdots + A_p y_{T+h-p} + C D_{T+h}$$

- The estimation of the A_i matrices can be done by OLS

$$vec(\hat{A}) = \begin{bmatrix} \hat{A}_1 \\ \vdots \\ \hat{A}_p \end{bmatrix}$$

- Under statiobarty and ergodicity condition for the VAR models (see Hamilton (1994), Lutkepohl (1991) among others), $vec(\hat{A})$ a consistent and asymptotically distributued with covariance matriz given by

$$\widehat{avar}\left(vec(\hat{A})\right) = \hat{\Sigma} \otimes (Z'Z)^{-1}$$

where

- $\hat{\Sigma} = \frac{\sum_{t=1}^T \hat{\varepsilon}_t' \hat{\varepsilon}_t}{T-K}$
- $\hat{\varepsilon}_t = Y_t - \hat{A}' Z_t = Y_t - \hat{A}' Y_{t-1}$ the residual at time t
- The i -th element of $vec(\hat{A})$ is asyntotically normal (for an a stable VAR) and the standrad error are the square roots of the diagonal elementes of $\hat{\Sigma} \otimes (Z'Z)^{-1}$.
- The t -test are asyntotically valids for the estimated coeficients
- Other important situation for the VAR models is the presencia of one or more unit roots y_j .
- From the point of view of the economic theory it mean th study of a lung run behavior plus the temporal dynamic of the series.

- **Cointegration:** The components of y_t are cointegrated of order d, b , denoted by $y_t \sim CI(d, b)$ if
 - All the components of y_t are $I(d)$; and
 - There exists a vector $\beta (\neq 0)$ such that $z_t = \beta' y_t \sim I(d - b), b > 0$. The vector β is called the cointegrated vector
- **Error correction:** The bivariate vector $y_t = (y_{1t}, y_{2t})'$ has cointegrated vector $\beta = (1, -\beta_2)'$, and $\beta' y_t = y_{1t} - \beta_2 y_{2t} \sim I(0)$ then, exist an error correction representation
 - $\Delta y_{1t} = \alpha_1 + \gamma_1(y_{1t-1} - \beta_2 y_{2t-1}) + \sum_{i=1}^K \psi_{1,i} \Delta y_{1t-i} + \sum_{i=1}^K \psi_{2,i} \Delta y_{2t-i} + u_{1t}$
 - $\Delta y_{2t} = \alpha_2 + \gamma_2(y_{1t-1} - \beta_2 y_{2t-1}) + \sum_{i=1}^L \xi_{1,i} \Delta y_{1t-i} + \sum_{i=1}^L \xi_{2,i} \Delta y_{2t-i} + u_{2t}$

The $VAR(p)$ model can be written

$$\Delta y_t = \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \dots + \Gamma_{p-1} \Delta y_{t-p+1} + CD_t + u_t$$

$$\Gamma_i = -(A_{i+1} + \dots + A_p), \quad i = 1, \dots, p-1$$

$$\Pi = -(I - A_1 - A_2 - \dots - A_p)$$

A Vector correction model (VECM) :[transitorio](#)

Or as:

$$\Delta y_t = \Pi y_{t-p} + \Gamma_1 \Delta y_{t-1} + \dots + \Gamma_{p-1} \Delta y_{t-p+1} + CD_t + u_t$$

$$\Gamma_i = -(I - A_1 - A_2 - \dots - A_i), \quad i = 1, \dots, p-1$$

$$\Pi = -(I - A_1 - A_2 - \dots - A_p)$$

VECM : [Lung run](#)

The matrix Π represent the lung run behavior and if:

1. $rk(\Pi) = n$, the n linear combinations are stationary; in other word the VECM is no more tha VAR model in levels
 2. $rk(\Pi) = 0$, there is no linear combination that makes Πy_{t-1} stationary, except for the trivial solution i.e., it becomes and $VAR(p-1)$ in first differences
 3. $0 < rk(\Pi) < n$, the most interesting case, we can write $\Pi = \alpha \beta'$ ($n \times r$) and $\beta' y_{t-1}$ is stationary. Each column of the matrix β represent a lung run relationship
-
- If the objective is to forecast series that are integrated or cointegrated doing with through a VAR representation is the most appropriated (see Lutkepohl 2006)

From the application:

- In the inflation example we specify the orden of the model through the final error prediction criteria, it was $p = 3$.
- We also performe Johansen test to determine the presence of lung run relationship. Finding the following relathionship which it was significant to 1%, level :
$$p + 9.68 - 0.43m_0 - 0.89y + 0.10r = 0$$
- This relationship is congruent with the economic theory behind it. The inflationary movement increases for the monetary grow, the exced on demand and the reduction on the money cost.
traspaso inflacionario está impulsado por el crecimiento monetario, exceso de demanda y la reducción del costo del dinero.

VAR-PLS

1. The VAR model will the the DGP
2. The VAR model will provide the autoregressive process that we will use to built the PLS regression
3. We built then the matrices in at natural way as:

- For the X matrix we include the lag vector: $X = Y_{t-1} = \begin{bmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p} \end{bmatrix}$ and
- For the Y the observed until time t $Y = Y_t = \begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{bmatrix}$ using the X with all the lags consider for the DGP.

- We can introduce exogenous variables with a C matrix, then $X = Y_{t-1}^* = \begin{bmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p} \\ D_t \end{bmatrix}$ and the

coeficient matrix with look like $A^* = \begin{bmatrix} A_1 & A_2 & \cdots & A_{p-1} & A_p & C \\ I & 0 & \cdots & 0 & 0 & 0 \\ 0 & I & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & I & 0 & 0 \end{bmatrix}$

- Those are the basic ingredients for a VAR-PLSX that will allows to predict h steps ahead

For the $VAR(p = 3) - PLS(h = 24, j)$

- We kept 24 observation to have a long horizon of possible comparisons
- We consider dummies for the monthly effects
- For the optimal p óptimo we estimate VAR-PLS, we use R to fit $Y_t (119 \times 4) = (Y_{t-1}, D_{t-1}) (119 \times 23) * B(23 \times 4) + U(23 \times 4)$ and predict for the $VAR(3) - PLS(24, j)$ in a recursive way as in the $VAR(p)$. According with Franses exercise, the last component agrees with the $VAR(p)$ OLS estimate
- For the $pK + g = 23$ components and the 24 out of the sample steps we get the MAPE to make the comparison

Para el modelo $VAR(p = 3)$,

- Combining all the variables estimate our $VAR_j(p), j = 1, \dots, 3696$
- For the 24 steps out of the sample we use 7 different criterias to measure the behavior of the forecast (Hyndman & Koehler 2006):
 - MAPE: Mean Absolute Percentage Error
 - MdAPE: Median Absolute Percentage Error
 - RMSPE: Root Mean Square Percentage Error
 - RMdSPE: Root Median Square Percentage Error
 - MRAE: Mean Relative Absolute Error
 - MdRAE: Median Relative Absolute Error
 - GMRAE: Geometric Mean Absolute Error

Note: For the last 3 we need to work with a benchmark model (autoregresie order 1) and for $i = 1, \dots, h$ ($h = 24$) obtain the statistic:

- $$test = \frac{Y_{t+i} - Y_{t+i, VARj(p)}^f}{Y_{t+i} - Y_{t+i, AR(1)}^f}$$

- With the 7 criteria, integrate to one by taking the 0.5 quantil for the horizon consider, repite it for their upper and lower confidence intervals.

Intervalo de predicción: VAR-PLS

- We also have to construct the prediction intervals for the VAR-PLS model.

We use a similar procedure to the one proposed by Pascual, Ruíz and Fresoli (2011). *Bootstrap forecast of multivariate VAR models without using the backward representation*. Working Paper 11-34, Statistics and Econometrics Series. They use the seminal ideas of Kim (2001) and some results from a previous work, Pascual, L., J. Romo, and E. Ruiz (2004a). Bootstrap predictive inference for ARIMA processes, Journal of Time Series Analysis, 25, 449-465

- For the VAR model they proposed a method that couples with:
 - 1) The uncertainty give by the estimation of the parameters, building confidence regions using their bootstrap method
 - a) *This regions are valid under Gaussian assumptions (Lütkepolh et al, 1991), even though do not reflect, for small sample size, the asymmetric distribution of the predicted values (under estimated parameters)*
 - 2) The backward representation makes calculations quite complicate more in the case of the VAR(p) representation and p taking values greater than 5 for example, which is very common.
 - a) *"Pascual et al shows that the backward representation can be avoided without loosing the good properties of the bootstrap procedure"*
- Of course we needed to adequate the procedure to the procedure to the VAR-PLS representation

Step 1. Fit the model to get $Y_t = X_t \hat{\beta}_{PLS}$

Step 2. Obtain the standarized residuals \hat{U}_t^* and get the empirical distribution of the residuals,

Step 3. With the p initial values $Y_0 = \{Y_p, \dots, Y_1\}$ and the values obtain in Step 1 and 2 generate Y_t^* , the bootstrap values, through were the \hat{U}_t^* are independent draws from its empirical distribution :

$$Y_t^* = X_t \hat{\beta}_{PLS} + \hat{U}_t^* \quad t = 1, \dots, n-p$$

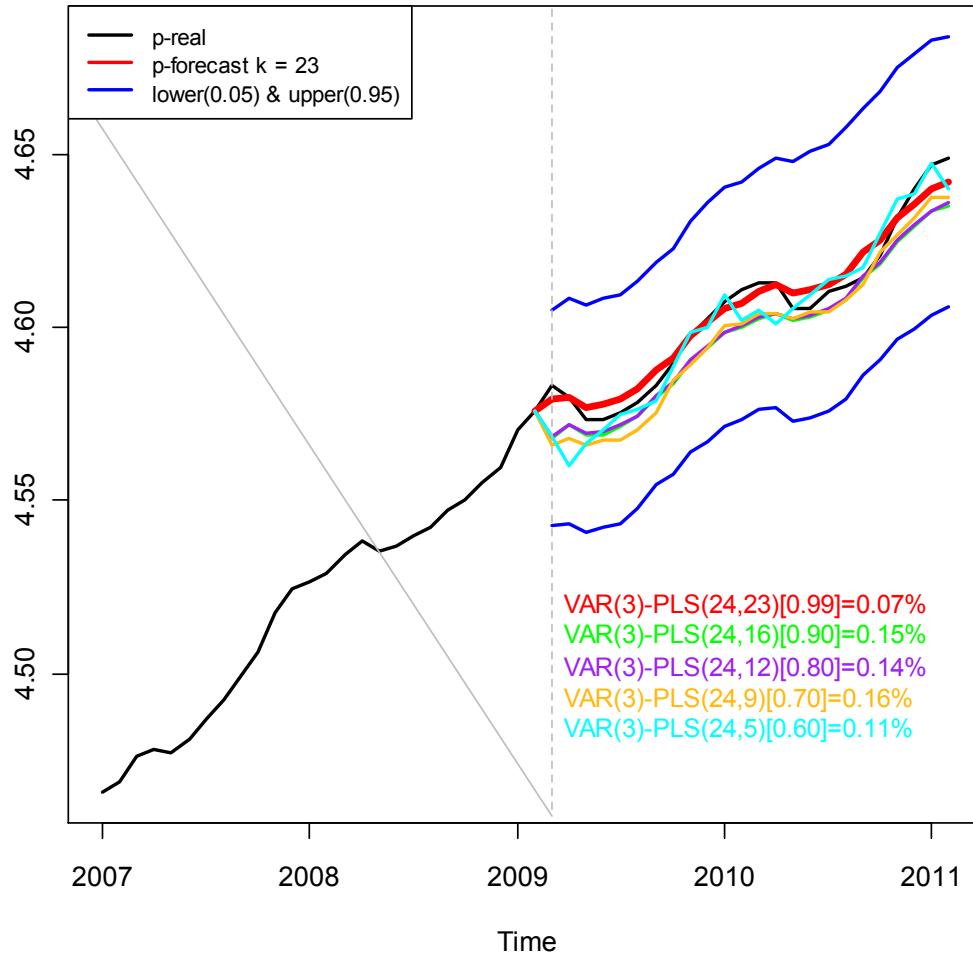
Step 4. We proceed in this way to get \hat{Y}_{T+h}^* replicating steps 2 to 4 for $n = 1, \dots, N$

Step 5. For each one of the n variables and the set of N forecast we get:

$$CI_{T+h} = \{y_{n,T+k} | y_{n,T+k} \in [q_B^*(\tau), q_B^*(\tau-1)]\}$$

where $q_B^*(\tau)$ is the τ th percentil of $G_{n,B}^*(x) = \#(y_{n,T+k}^{*(b)} \leq x)/N$

Forecast series p: VAR(3)-PLS(h=24,k)



- From the economic point of view, the approximation is excellent.
- We observe that either using, $k = 23$ (0.99 of the variability) with an error percentage of 0.07% or with 70% explanation with an error percentage of 0.16%, the real value and the predicted one, for practical purposes are almost identical.
- The bootstrap interval is very well behaved.

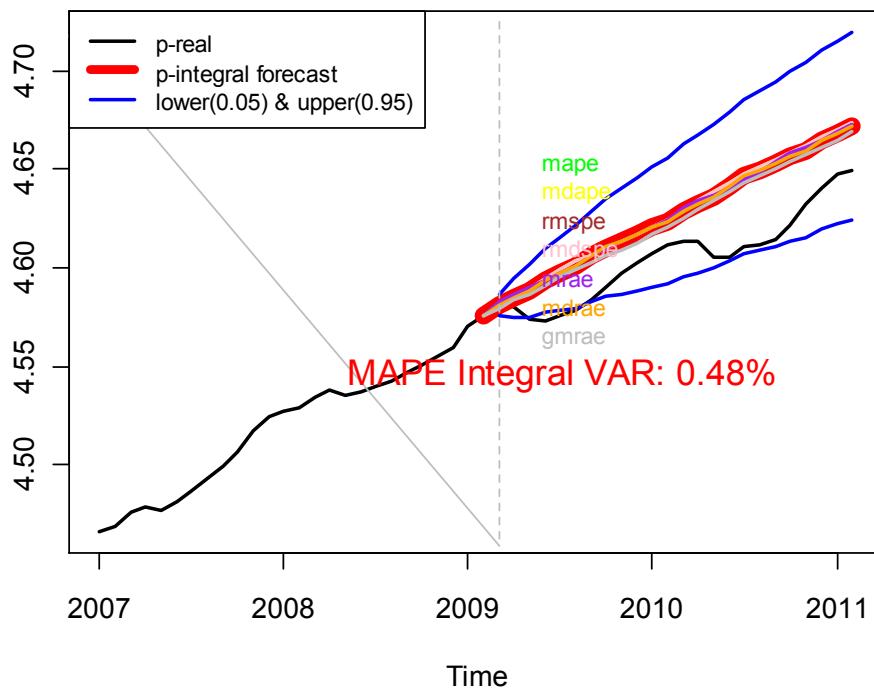
NOTA: The objective is to forecast the price, however since it is a multivariate model we also get forecast for the other 3 variables with forecast error(Average of MAPE) of : **0.20% for the**

monetary base, 0.60% for industry production index and 12.03% for the equilibrium interest rate.

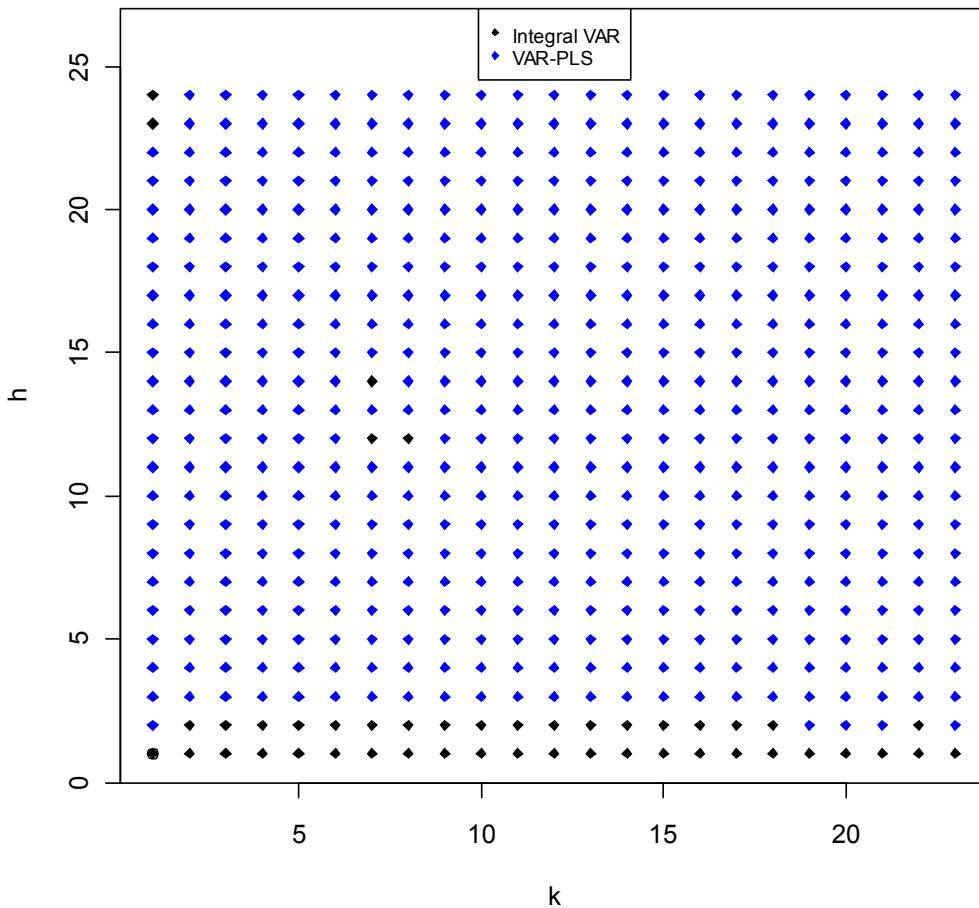
For the integral-VAR, the optimum $VAR_j(p)$ are:

Criteria	MAPE	MdAPE	RMSPE	RMdSPE	MRAE	MdRAE	GMRAE
Statistic	0.16	0.12	0.19	0.12	0.16	0.12	0.11
Variable	r	r	r	r	r	r	r
lags	3	2	3	2	2	3	5
Stacionality	9	11	9	11	6	9	11
Specification	none						

Forecast series p: Integral-VAR



Integral VAR vs VAR-PLS (Comparasion with MAPE)



In average **91.67%** the PLS representation of the VAR over all the components. It make sense that the last components are less effective.

The VAR-PLS seems to be an attractive competitor of the, **integral VAR which is constructed for prediction purposes, with the advantage of a confidence intervals that include the uncertainty due to the parameter estimation.**

Conclusiones

- We present an alternative forecast algorithm for a multivariate framework, that takes into account the dependencies among the series (y_{t+j} with y_t), through a PLS model written as a linear model with X having the VARX representation.
- The empirical result for the Mexican inflation are quite appropriate from an economical point of view
 - VAR-PLS was built with p given from the fit of a VARX, estimating in this case, all the pK possible components

- We construct the prediction interval using a Bootstrap method
- The VAR-PLS is an attractive multivariate technique to forecast this type of data.

Future work:

- Look for the implicit relationship between cointegration (CCA) and PLS
- Build a *PLS-VAR* without fitting the VAR model and compare its forecast with the integral VAR model.

REFERENCES

1. Bjorn-Helge Mevik and Ron Wehrens The pls Package: Principal Component and Partial Least Squares Regression in R, Journal of Statistical Software January 2007, Volume 18, Issue 2. <http://www.jstatsoft.org/>
2. Carreiro, Kapetorios & Marcellino (2010), Forecasting Government Bond Yields with large Bayesian VAR's. Working papers No. 662 School of Economics and Finance.
3. Esposito Vinzi, V., W.W. Chin, J. Henseler and H. Wang (2007), Handbook of
 - a. Partial Least Squares, Berlin: Springer.
4. Philip Hans Franses(2006) Forecasting 1 to h steps ahead using partial least squares
5. Econometric Institute, Erasmus University Rotterdam, Econometric Institute Report 2006-47
6. P.H. Garthwaite (1994). An Interpretation of Partial Least Squares. JASA Vol 89, No 425, pp122-127
 - a. Hoskuldsson (1988). PLS Regression Methods. Journal of Chemometrics, Vol 2, pp 221-228.
7. Kim, J.H. (2001), Bootstrap after bootstrap prediction intervals for autoregressive models, Journal of Business & Economic Statistics, 19(1), 117-128.
8. Lutkepolh, H. (1991), Introduction to Multiple Time Series Analysis, 2nd ed., Springer-
a. Verlag, Berlin.
9. Lutkepolh, H. (2006), Forecasting with VARMA models, in Elliot, G., C.W.J. Granger and
10. Timmerman (eds.), Handbook of Economic Forecasting, Vol. 1, 287-325.
11. McIntosh A.R., Bookstein F.L., Haxby J.V. and Grady C.L. (1996). Spatial Pattern Analysis of Functional Brain Images Using Partial Least Squares NeuroImage, Volume 3, Number 3, pp. 143-157(15). Academic Press
12. Marcellino, Stock & Watson (2004), A Comparison of Direct and Iterated Multistep AR Methods for Forecasting Macroeconomic Time Series.NBER
13. Paul Nomikos and John F. MacGregor (1995) Multivariate SPC Charts for Monitoring Batch Processes *Technometrics* Vol. 37, No. 1, pp. 41-59 
14. Pascual, Ruiz y Fresoli (2011). *Bootstrap forecast of multivariate VAR models without using the backward representation*. Working Paper 11-34, Statistics and Econometrics Series,
15. Pascual, L., J. Romo, and E. Ruiz (2004a). Bootstrap predictive inference for ARIMA processes, *Journal of Time Series Analysis*, 25, 449-465
16. Pesaran, H. H., Pick, A., Timmermann, A. (2010). Variable Selection and Inference for Multi-period Forecasting Problems. *Journal of Econometrics*
17. Tiao, G.C., and D. Xu (1993), Robustness of maximum likelihood estimates for multi-step predictors: the exponential case, *Biometrika*, 80, 623-641

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