ECONOMIC ANALYSIS

BBVA-UHFAI: Ultra High Frequency Activity Index

A State Space Approach to Real Time Analysis of Economic Activity using Big Data

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Summary
We would like to present a particular framework for measuring economic activity in real time. This approach carries two distinct features: its ability to exploit ultra-high frequency information by means of state space modeling and the introduction of a novel set of semantic-based variables extracted by means of Big Data. We will try to show how this approach not only allows a real time gauge of the business cycle that actually improves the nowcasting ability of our legacy methods (MICA-TK) but also how our novel dataset –as it is assumed to depict economic uncertainty- contributes to the informative charge of our framework and improves its now-casting ability of economic activity. We will apply this for the case of Turkey.

Motivation
A timely assessment of the aggregate business conditions is cornerstone for sound policy analysis, strategic planning, financial trading and so forth. A common practice to grapple them is by means of inspecting national accounting constructs or confidence and activity indicators. However in using standard metrics like those one must always trade-off timeliness and informative power for grasping economic pulse. Meanwhile other more timely sources of activity information (financial variables mostly) are rarely factored-in in the daily grasp of the economic momentum basically due to the absence of a suitable framework. On the other hand, gauging more qualitative economic drivers not embedded in hard data remains elusive and foremost confined to the use of medium frequency confidence indicators what arguably brings us back to the previous trade-off dilemma.

Against this backdrop we present a framework for real time assessment of activity cycle in the spirit of Stock and Watson (2002), Marcelinho (1991), Mariano & Murusawa (2003) and Auroba Diebold & Scotti (2007) among others. Our framework has four distinct features:

1. Business cycle conditions are treated within a dynamic factor model as unobserved variable bound to the co-movement of many activity indicators, preserving the spirit Lucas (1977) among others.
2. Un-observed or latent point-in-time activity is gauged at four frequency levels (quarterly, monthly, weekly and daily) in an attempt to minimize the time-representability trade-off mentioned above.
3. We incorporate a continuously evolving activity related indicator that –for the sake of clarity- we render to daily frequency slots, although it could arguably be exploited at even intraday frequencies.
4. A new collection of qualitative variables are proved to be informative in assessing real business conditions. Their informative charge is intimately related to the findings of Bloom (2013, 2016) in portraying the effect of policy and economic uncertainty onto activity. This variables are synthetized after querying the Global Database of Emotions Location and Tone (GDELT) proprietary work of Kalev Leetaru

The rest of this document goes as follows. Part 1 is devoted to explaining the methodology, treatment of missing observations, the model in its state space representation and its estimation. In part 2 a description of the work data base will follow. Attention will be paid to the construct of our economic and policy uncertainty daily indicators by means of Big Data analysis. In Part 3 we will show results, we will show the ability to gauge the economic cycle using different set ups and will give some metrics of the quality of our estimations. Part 4 will conclude and open possibilities for further research. Your takeaway will be that: “real time forecasting of activity is possible”. And you will learn that our novel dataset of policy uncertainty indexes improves the now-casting ability of our endowment bis a bis alternative set ups within the same framework while it helps bridging the link between economic performance and economic, policy and political uncertainty á la Bloom.

The latter however should not obliterate the fact that our legacy lower frequency state space model (namely our “MICA-TK” which is a monthly instrument for nowcasting Turkish GDP) still outperforms any our UHFAI models when use simple monthly activity indicators such as IPs or PMIs as the former is specified with many more variables. We circumvent this undertaking a two-step approach namely first estimating the monthly state space model (the MICA-TK) which exploits thirteen activity indicators to obtain a single latent factor of activity and then using this extracted latent factor as monthly activity indicator among our varied frequency set up of the UHFAI.

Theoretical Background

We assume that the state of the economy evolves at a very high frequency agreeable in daily quotes. In the same vein, we assume that all feasible economic, qualitative and financial variables also evolve on a daily basis though not all of them are observable at this frequency but at lower ones. For instance we could have daily quotes of a yield spread speaking for economic expectations or any related measure, combined with unobserved realizations of industrial output and stock of credit only observable at the monthly (output) or even weekly basis (credit) altogether running along continuous realizations of gross domestic product that only see their realization on a quarterly basis. Some of these variables come with seven, thirty, sixty or even ninety days delay to the current economic momentum.

Aggregation and not approximation

Allow $(y*_{it})$ to represent daily quotes of our variables and (y_{it}) to denote the same variables at their corresponding (lower or not) observable frequencies. The relation between both will depend whether $(y*_{it})$ a stock variable or a flow variable is. Employment figures or credit are stock variables as they aggregate continued realizations new employees or new credit operations conceded for instance. In that case we have for the stock (1) and flow (2) variables

$$(1) \quad y_{it} = \begin{cases} y*_{it} & if\ observed\ point\ in\ time \\ |\emptyset| & else \end{cases}$$

$$(2) \quad y_{it} = \begin{cases} f\left(y*_{it,}\, y*_{it-1,} \dots y*_{it-Di}\right) & if\ observed\ as\ flow \\ |\emptyset| & else \end{cases}$$

Where $(D_i)\ i \in \{\{1,\dots,n\}$ denotes the number of days for the temporal aggregation. We impose for this exercise D to be fixed at the maximum range of unobserved dates possible. These would rise up to [90][1] applicable to the dynamics of explanatory variables in the transition block of our model. This is important because will permit exact aggregation inter observation of the unobserved variables, a distinct feature to the standard approach of Mariano and Murusawa (2003) where higher to lower frequency relations are bound to polynomial approximations (recall MM’s lag polynomial $(P[x])$, $y_{1t} = \frac{1}{3}(x_{1t} + 2x_{1t-1} + 3x_{1t-2} + 2x_{1t-3+} + x_{1t-4})$ where y and x are quarterly and monthly quotes for example) which are not feasible here since we work with daily frequency and the measurement state matrix will have unfeasible order for this kind of exercise.

The Model

We impose the latent economic cycle or business conditions (x_t) to pursue the dynamics of an autoregressive process of order (p) on a daily frequency, be that any kind of activity or expectations related variable

$$(3) \quad x_t = \rho_1 x_{t-1} + \dots + \rho_p x_{t-p} + v_t \quad where\ v_t \sim N(0,1)$$

And assume all economic variables $(y*_{it})$ evolve daily yet might not necessarily be observed (daily), linearly depending on the set of explanatory variables (x_t) and possibly exogenous variables (z_t) as well as $(y*_{it})$ own lagged dynamics to the possible order D. As such we have:

$$(4) \quad y_{it} = c_{1+}\beta_i x_{it} + [\delta_{i1} z_{i1t} + \dots + \delta_{ik} z_{ikt}] + [\alpha_{i1} y_{it-Di} + \dots + \alpha_{i1} y_{it-k-Di}\ ] + u_t \quad where\ u_t \sim N(\mu,\sigma)$$

And where we can see (according to (1) and (2)) that the persistency of our activity measure is linked to the observed variable, normally at lower frequencies. This is important to limit the speed of decay of the time series process. Equation (4) is the measurement equation for all stock variables. And given our temporal aggregation of flow and stocks displayed above and after working out the exogenous variable part as deterministic trend the relation between observed flow variables the factors it follows equation (5), our measurement equation for the relation between flow and stock variables.

[1] That brings 89 lagged unobserved quotes for the forthcoming transition equation of the model to be generalized to all candidate variables even if they have higher frequencies

$$(5)\quad y_{it} = \begin{cases} \sum_{j=0}^{Di-1} c_i + \beta_i \sum_{j=0}^{Di-1} x_{it-j} + \delta_i \sum_{k=1}^{k} t^k + \alpha_{in} y_{it-nDi} + u_t^i & if\ y_{it}\ is\ observed \\ |\emptyset| & else \end{cases}$$

State Space Representation

Given the general form of the relation between observed and unobserved stock and flow variables we may stack the model in the usual state space representation where 6a is the stacked version of our previous measurement equation system and 6b the transition system from the latter.

$$(6a)\quad \begin{bmatrix} y_{1t} \\ \cdots \\ y_{kt} \end{bmatrix} = H_t S_t + \Gamma_t\, w_t + \varepsilon_t \qquad where\ \varepsilon_t \sim N(0, H_t)$$

$$(6b)\quad S_t = F S_{t-1} + R\eta_t \qquad where\ \ \eta_t \sim N(0, Q)$$

Here, $t \in \{\{1, \dots, T\}$ where T denotes the last time-series observation, c is an N×1 vector of observed variables, (H_t) is an m×1 vector of state variables, (w_t) is a e×1 vector of exogenous variables, and εt and ηt are vectors of measurement and transition shocks which will collectively contain (vt) and (ut). From equations 3 and 4. The exact structure of these vectors will vary across the different setups that we could consider.

Recursive Estimation

With the model casted in state space form, we can apply the Kalman filter and smoother. Kalman filter supplies all of the ingredients needed for evaluating the Gaussian pseudo log likelihood function via the prediction error decomposition.

$$(7)\quad Log\ L = -\frac{1}{2}\sum_{t=1}^{T}[N \log 2\pi + (\log|F_t| + v_t' F_t^{-1} v_t)]$$

In calculating the log likelihood, if all elements of $(y*_{it})$ are missing, the contribution of period t to the likelihood is zero. When some elements of $(y*_{it})$ are observed, the contribution of period t is $[N \log 2\pi + (\log|F_t| + v_t' F_t^{-1} v_t)]$ where N is the number of observed variables and the other matrices and vectors are obtained using the Kalman filter recursions on the modified system with the next observed (y_{it})

Knowing how to evaluate the log likelihood for any given set of parameters, we estimate using a quasi-Newton optimization routine with BFGS updating of the inverse Hessian. However given the paramount size of the needed identification we opt to circumvent brute force estimation of that huge state vector using an aggregator states to handle the lags of the indicator for the two flow variables. This requires changing the transition matrix to zero out the aggregator when we get an observable for the flows (in or case credit and GDP).

The Data

This sort of approach stands rather close to the strand of literature related to small data sets. As such, and given the exponential complexity of specification of the transition matrix when additional explanatory variables are included, we need to stick to a very narrow format of the *One Factor Small*[2] *Scale Dynamic Factor Model* in the spirit of the seminal work of Stock and Watson (1989 1991) and further developments by Perez Quirós (2010). To encompass this we will relate to an analysis that exploits information from a single indicator from each possible frequency: quarterly, monthly, weekly and daily. (Please See appendix for displays of the Data)

Quarterly: GDP is reported on a quarterly basis and with 60 to 90 days delay. Our main goal is to estimate unobserved realizations of this within its frequency range with the help of our latent factor. We will work with quarter on quarter growth rates of this variable. Our quarterly quotes are taken from 1998 Q1 up to 2015 Q3

[2] We exploit 13 dependent variables while in Large Scale Factor Models normally 200 hard and soft data indicators are used, see Gione 2008 for example

Monthly: we will exploit and contrast an array of alternative monthly activity indicators such as **Industrial Production**, **Electricity Demand** and **the PMI of manufacturing** and more importantly **the latent factor of our legacy activity factor model for Turkey (MICA)** All these indicators are reported on a monthly basis since 2005 but with different delays (ragged ends) except for the MICA which is nowcasted to the current month.

We will use monthly rates of these variables in different model set ups and confront their forecasting ability bis a bis the MICA to motivate the gain in model richness and forecasting power when using the latter. The results however will only depict the outcomes of the set up using the latter as all informative metrics override the use of any alternative monthly indicators (recall that MICA-TK synthetizes the information of all alternative indicators).

Weekly. Weekly quotes of FX corrected credit stocks are used to gauge demand activity since 2002. We will use these but alternatively employment creation quotes could be used instead. All our weekly quotes are taken until January 31st 2016

Daily in order to implement our ultra-high frequency framework we will run our analysis with two possible candidates of semi continued variables: financial variables and qualitative uncertainty indexes.

- **Financial Variables.** Standard literature uses quotes of the **term premium** in order to gauge an anticipated insight of economic dynamics[3] we gather this by subtracting a short term rate treasury rate to a longer one (10 yr -2 yr treasury rates[4]) Additionally we will also try a **the 3M market fx implied interest** rates to compare the informative split between both as besides term premium considerations liquidity issues in foreign currency are very relevant in certain emerging markets like Turkey. Interest rates and spreads are taken on daily basis since January 1st 2005 until January 31st 2016.

- **Qualitative uncertainty indexes.** Despite the power of the aforementioned variables to gauge expectations or liquidity issues they fail to gauge the influence of different types of uncertainty onto activity. It has been well documented (Baker, Bloom and Davis 2013 & Bloom 2016) that uncertainty has paramount influence in the dynamics of activity. To gauge this effect we will exploit a collection of Big Data based qualitative variables rendered as synthetic uncertainty indicators and its subcomponents. These indicators have the temporary caveat of having a rather modest informative past: they exist only since April 2013 (until the author expands the sample, presumably soon) and run until today. But for the sake of consistency we will use only data until January 31st 2016. **Please see appendix for details**.

  An alternative to the latter would have been to try to exploit some sort of risk premia but we avoided this as risk premia are strongly procyclical and currently strongly conditioned by the compression yields in safe haven assets as a result of flight to quality.

Estimation Strategy and Results

We run the estimation of our UHFAIs with different specifications yet always circumscribing the restriction about the number of indicators stated above (only one indicator per frequency).

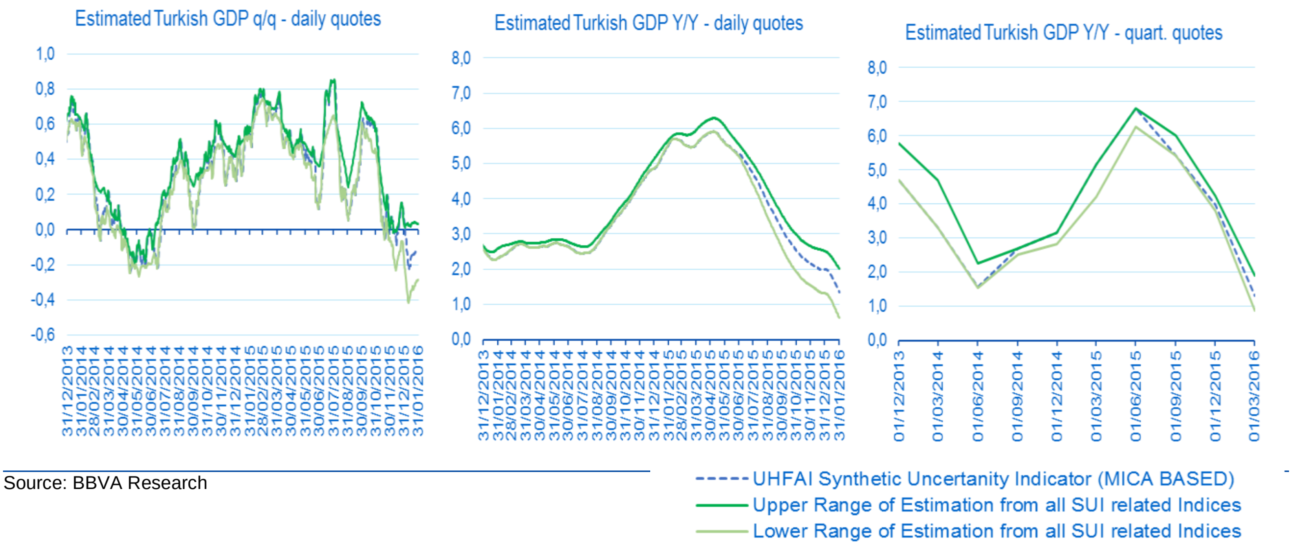
We precede leaving the quarterly based indicator (the GDP in q/q rates) and the weekly quoted Credit Stock fixed and we try alternative combinations of daily and monthly indicators. More specifically we run models using GDP, Credit, alternatives of monthly indicators and the components of our BBVA Uncertainty Indicator. Among the alternatives of monthly indicators we try IP, Electricity Demand, PMI and finally the latent factor of the MICA. To undertake the latter we need first to extract the monthly latent activity signal by means of factor modeling and then use the estimated estate (or the latent component) as monthly indicator of our UHFAI (instead of the alternative monthly indicators)

Accordingly, we also run two types of exercise using alternative daily quotes of financial variables as they are also supposed to gather qualitative information about expectations In this regard, we try again IP, Electricity Demand, PMI of manufacturing and our synthesis indicator MICA TK swapping the two daily financial

[3] As its actually the slope of the term structure what hints expectations on the economic cycle
[4] Actually we will combine the Treasury rates from Mar-2010 to present (as 10 yr note was first issued in Jan-2010.) and extend it up to 2005 using the swap rate for the same maturity

indicators: 3M implied TL rates on USDTRY forwards and the term premium or slope of the yield curve.

Figure 1
Uncertainty Based - UHFAIs [daily and quarterly quotes of estimated GDP growth]



Source: BBVA Research

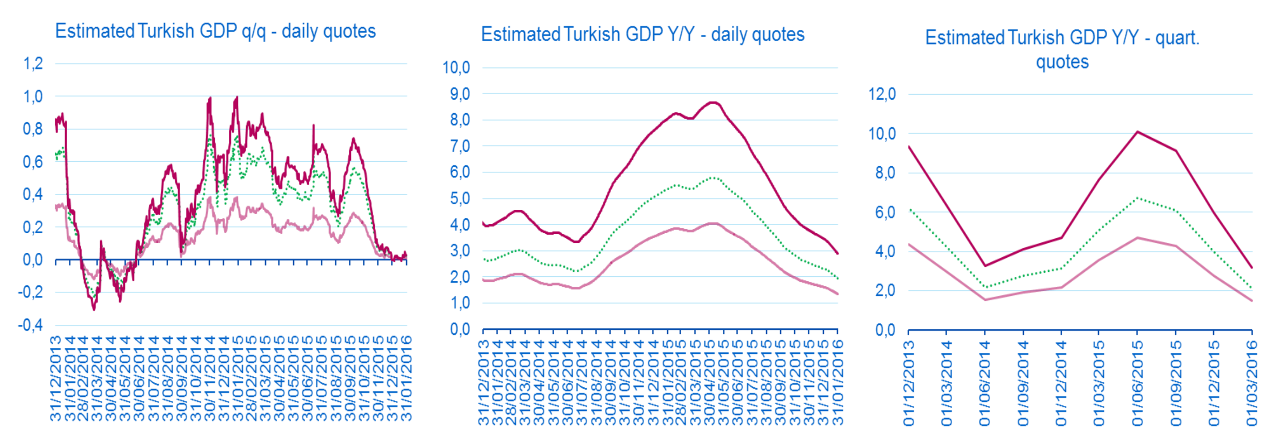
In total we have 28 versions of the model with various alternatives of high and medium frequency indicators. Each time the Dynamic Factor Model is estimated by means of Kalman with a diffuse prior. The process needs implicitly not only to estimate the parameters of the measurement equation but also three lags of ninety observed and unobserved quotes of the four variables that compose the model (this is the reason why we constrain the specification so much) so for each block of daily quotes (financial or uncertainty) we depart to the estimation of the next case from the already estimated betas of the previous model. This trick at least allows us to find a stable local optimum.

Above (chart 1) we portray median and band outcomes of the estimations of the GDP on a daily basis presented in quarter on quarter and year on year growth. Bands represent the maximum and minimum range in the estimations retrieved after running the 20 different versions of the model stated above. The dotted lines in the middle correspond to a chosen activity indicator from the 20 different alternatives which is the one using the MICA-TK latent factor as monthly indicator. We have selected that specifically as it has the best readings in terms of tow metrics the Log Likelihood and the Semi Out of the Sample RMSE presented at the appendix. This winning indicator was expected is the one that uses a synthesis compound of all uncertainty groups jointly with the latent factor of the MICA model, Credit and GDP. *We will call this one UHFAI_SUI (High Definition Index with Synthetic Uncertainty Measure)*

For comparison we repeat the same exercise with financial variables - based daily indicators. Below (Chart 2) we show daily estimations of the GDP on a q/q and y/y rates. Here we display maximum and minimum values of all possible candidate combinations using the two alternatives. In total we summarize six different combinations whereas the inner dotted line is the selected indicator according to the same performance metrics explained above. The selected indicator once again, uses the latent factor of our MICA-TK model rather than any of the alternative monthly variables alone (PMI and Electricity Demand and IPs) combined with the daily quotes of implicit 3M rate swap rates. *We will call this UHFAI_ 3M (High Definition Index with 3 month swap interest rate)*

Comparing both sets (financial and uncertainty) we find that estimations of the GDP on a daily basis are clearly differential depending of the information used being those who exploit uncertainty the ones that get their point in time estimations of GDP growth more penalized. We attribute this to the fact that whereas the latter (UHFAI_3M) gathers expectations and uncertainty on economic performance, the former (HDI_SUI) additionally gathers other sources of concern not factored-in in market expectations (such as uncertainty on global financial conditions or politics). For instance, average daily quotes of growth YoY and QoQ succeeding the stint of the taper tantrum (Q1 2014) are -0.1% yoy in the HDI_ 3M while the record -0.2% in the UHFAI_SUI. The two periods of political turmoil namely the Gezi Park protests and succeeding weeks (c.a Q1 2014) and the first election period (c.a Q2 2015) are characterized by weaker growth estimations when using the HDI_SUI, to name a few stylized facts.

Figure 2
Financial Variables Based UHFAIs [daily and quarterly quotes of estimated GDP growth]

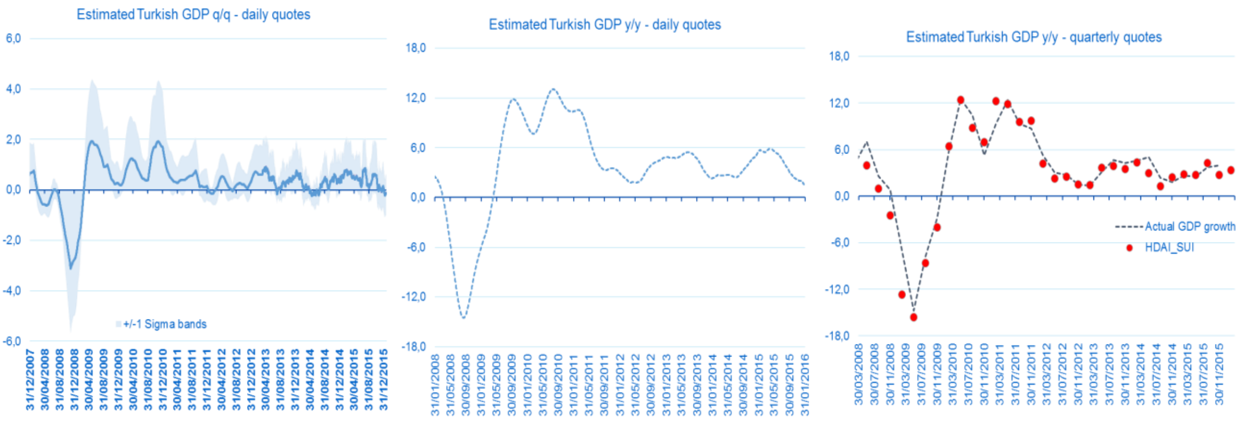


Source: BBVA Research

UHFAI_3ML (MICA BASED)
Upper Range of Estimation from all Financial related Indices
Lower Range of Estimation from all Financial related Indices

On inspection of the quarterly induced growth rates (derived from the daily GDP growth quotes) given on Chart 5 compared with the actual growth register we see that the MICA based UHFAI_SUI outperforms UHFAI_ 3M as the in sample fit to the actual growth data are better. Also, inspecting the out of the sample RMSE and the DM metrics from the summary tables 1 to 3 we derive the same conclusions. We find that the out of sample forecast ability of this one is also better. A reason to believe in the informative power of our Big Data Based Uncertainty Indexes that exploit the latent factor of our MICA-TK model.

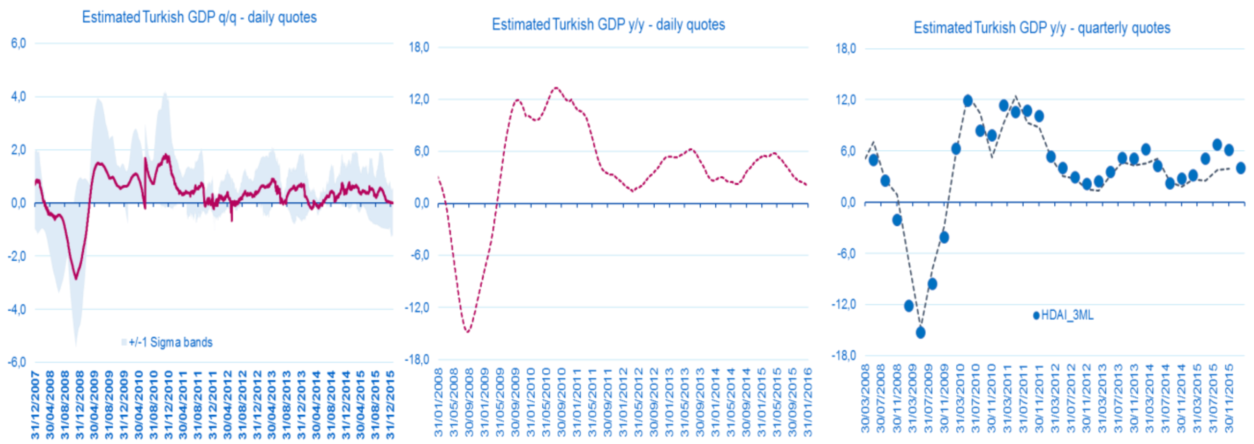
Figure 3
GDP Growth Estimation and UHFAI_SUI (MICA Based)



Source: BBVA Research

After reviewing the features and stylized facts of both candidate UHFAIs we have concluded the Policy Uncertainty Based UHFAI that uses the MICA outperforms not only same nature contenders (those using uncertainty) but also financial based UHFAIs. This holds in terms of quality (log likelihood of Eq. 5) but also in out of sample forecasting power. This we consider is an upside for an indicator that not only measures activity in real time in a rather parsimonious way but also that attributes the effects of various sources of uncertainty to growth.

Figure 4
GDP Growth Estimation and UHFAI_3ML (MICA Based)

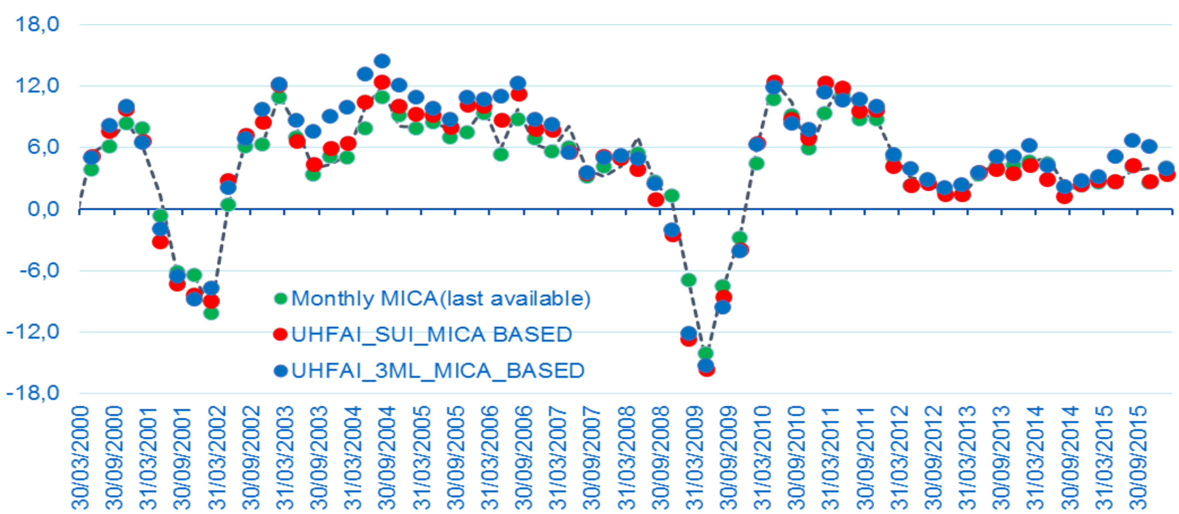


Source: BBVA Research

On inspection of table 1 in the appendix we find that none of the simple UHFAIs beat the forecasting ability of higher size in specification that mixing different sets of monthly information as the MICA does. The forecasting ability is made by means of a semi out of sample forecasting scheme as the kalman estimation process needs to estimate once the parameters for the global model and on each interaction the states are updated with the next step incoming information. Running a purely out of sample procedure is to our knowledge unfeasible when using a state space approach as it would mean recursively maximizing the log likelihood of the entire model, something for what our computing program is not prepared. Alternative forecasting procedures such as using Theil U are only suitable for Least Square Estimation of vector autoregressions and not for state space models.

Chart 5 depicts true realizations of yoy GDP growth vs. estimations made using MICA-based and UHFAI_SUI and UHFAI_3ML bis a bis the mothly estimates of while Table 1 confronts RMSEs of our MICAs based UHFAIs (with and without uncertainty based indicators) bis a bis the forecast of our standard MICA monthly version .

Figure 5
GDP Growth Estimation and actual Growth Rates (yoy in %) UHFAI_SUI & UHFAI_·3ML vs MICA estimates



Source: BBVA Research

Summing Up

We presented an ultra-high frequency activity indicator that mixes daily weekly monthly and quarterly data. This new activity indicator can exploit a novel set of qualitative indices to asess economic uncertainty which we find that improve the forecasting ability of the model. The model when using simple activity monthly indicator runs shorter in forecasting ability than traditional monthly factor models but we have circumvented this problem undertaking a two-step approach: we estimate first a factor model that gathers information from many more monthly indicators and use the latent activity signal as monthly activity indicator of our UHFAI. By doing this we find that our UHFAI version of activity factor model beats in forecasting ability legacy models, improves in forecasting ability when using uncertainty information and has the very distinct feature of producing daily estimates of the GDP.

Appendix

The BBVA Economic and Policy Uncertainty Index

Our Macroeconomic and Policy Uncertainty Index and its relation to the high frequency estimation of the GDP leverages strongly on the seminal work from Auroba Diebold and Scotti 2009 and Scotti, 2015 where a link between high frequency estimation of GDP and the macroeconomic uncertainty was been defined. It exploits agents anticipation of future states of the economy and their effect on activity under three different approaches either related to the theory of "new's" and uncertainty effects

1. Output effects as the result of an entirely psychological phenomenon where over/under realization of events bring boom and bust cycles that not supported by fundamentals like in Pigou 1927
2. Expectations Theory - led Self-fulfilling expectations and their effect on output a la Keynes 1936
3. Agent anticipation of future economic conditions a la Bernanke 1983 also analyzed as detrimental output effects from Economic, Political and Policy uncertainty (seminal references in Friedman 1968, Rodrik 1991 and Higgs 1997).

Operatively this indicator is a cross-over topic (not news based) indicator that drinks from Bloom' Economic Policy Uncertainty Index, "EPU" (2013, 2016) work and Larsens & Thorsrud's Topic Uncertainty Measures (2015, 2016). It exploits the idea that there is a stream of qualifying topics that build variables (uncertainty indexes) that tap onto activity via the financial or the expectations channel (increased costs of capital, expectations on output investment and employment, a la Bamburen and Reichlin 2010).

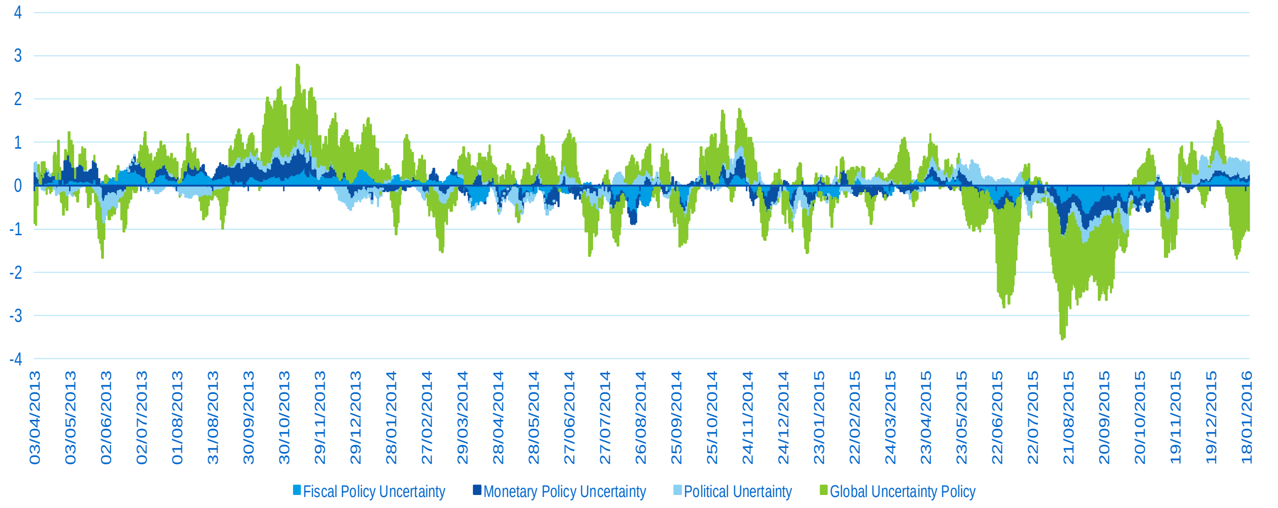
Like in Larsens and Thorsrud 2015 the indicator is a compound measure of interrelated tranches of topics that have been categorized within an information corpus, yet in our analysis we did not use a Natural Language Algorithm[5] to group these topics but rather allowed our expertise to make educated guesses on what indicators should qualify. Their effect on output however has been guided like in Thorsrud 2016 by means of a Dynamic Factor Model s explained above in the document.

The BBVA Uncertainty Index is a Principal Component-based synthesis indicator that stacks and matches the first principal component of different groups of uncertainty proxies for fiscal, monetary, external and political uncertainty. These proxies are extracted by means of Google Big Query from the Global Database of Emotion Location and Tone (GDELT) proprietary work of Kalev Leetaru (see www.gdelt.org for details). This database virtually screens, systematizes all possible digitalized media quotes on any issue found in the internet by means of Natural Language Algorithms (Tabari/Petrarch from Schrodt 2013). Extracted information is bond to a scoring that relates to the emotional charge of each screened quote by means of the so called Goldstein Scale (Goldstein 2009).

What we basically do is extracting proxies from quotes relative to different aspects of economic, political and policy uncertainty relative to a country and its global endowment. Quotes and their group of uncertainty gauged range from Fiscal and Monetary Policy Uncertainty, Political Distress and uncertainty over Global Financial and Economic Conditions (see Figure A1 for a detailed description). All of the extracted components are ultimately rendered into a single metric: *The Economic and Policy Uncertainty Index* whose building blocks are the different dimensions of uncertainty described above in a stack-wise manner. The synthesis indicator and all its subcomponents (see charts A2 to A5) can be retrieved intra-day (even each 15 minutes) but we exploit only daily quotes in this analysis.

[5] Dirchlet Allocation Algorithm

Figure 1
Historical decomposition of the index by components (daily basis)
Media coverage by sort of components related with Turkish politics

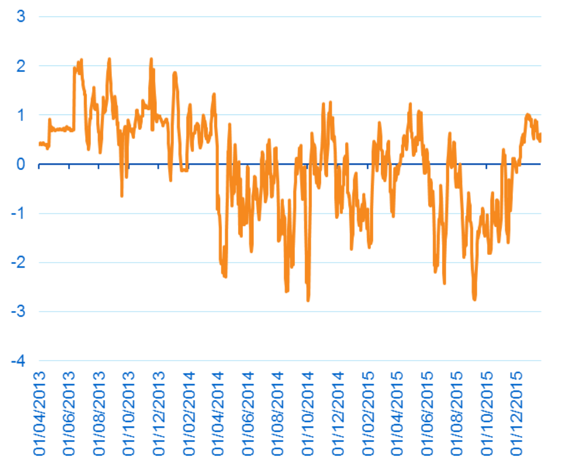


Source: BBVA Research and www.gdelt.org

Figure A1
Input table

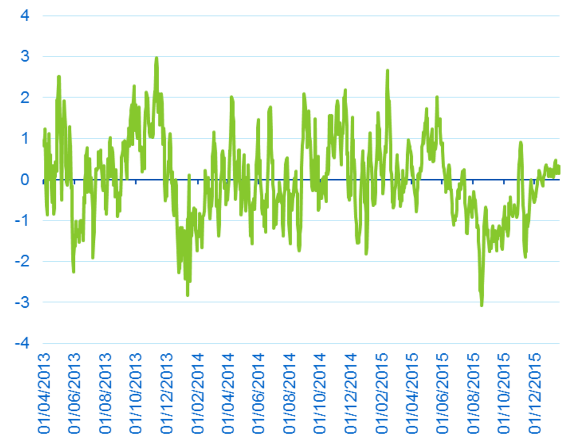
Fiscal Policy Uncertainty	Monetary Policy Uncertainty	Political Uncertainty	Global Uncertainty Policy
PRIVATIZATION	ECON_INTEREST_RATES	GOV_REFORM	ECON_INTEREST_RATES for US
AUSTERITY	ECON_COST_OF_LIVING	GENERAL_GOVERNMENT	ECON_INTEREST_RATES for EU
ECON_DEBT	ECON_CURRENCY_EXCHANGE_RATE	TAX_POLITICAL_PARTY	ECON_INTEREST_RATES for China
ECON_SUBSIDIES	ECON_CURRENCY_RESERVES	ELECTION	ECON_STOCKMARKET for US
ECON_TAXATION	ECON_HOUSING_PRICES	POLITICAL_TURMOIL	ECON_STOCKMARKET for EU
	FUELPRICES		ECON_STOCKMARKET for China
			ECON_CURRENCY_EXCHANGE_RATE for US
			ECON_CURRENCY_EXCHANGE_RATE for EU
			ECON_CURRENCY_EXCHANGE_RATE for China

Figure A2
Fiscal Policy Uncertainty Component Index



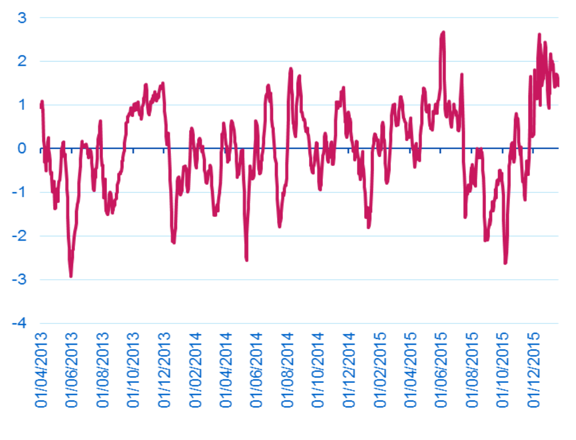
Source: BBVA Research and www.gdelt.org

Figure A3
Monetary Policy Uncertainty Component Index



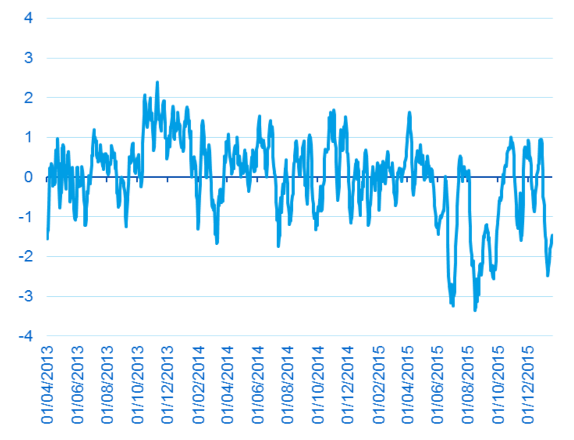
Source: BBVA Research and www.gdelt.org

Figure **A4**
Political Uncertainty Component Index



Source: BBVA Research and www.gdelt.org

Figure A5
Global Uncertainty Policy Component Index



Source: BBVA Research and www.gdelt.org

Figure A6
Synthetic Index: political uncertainty

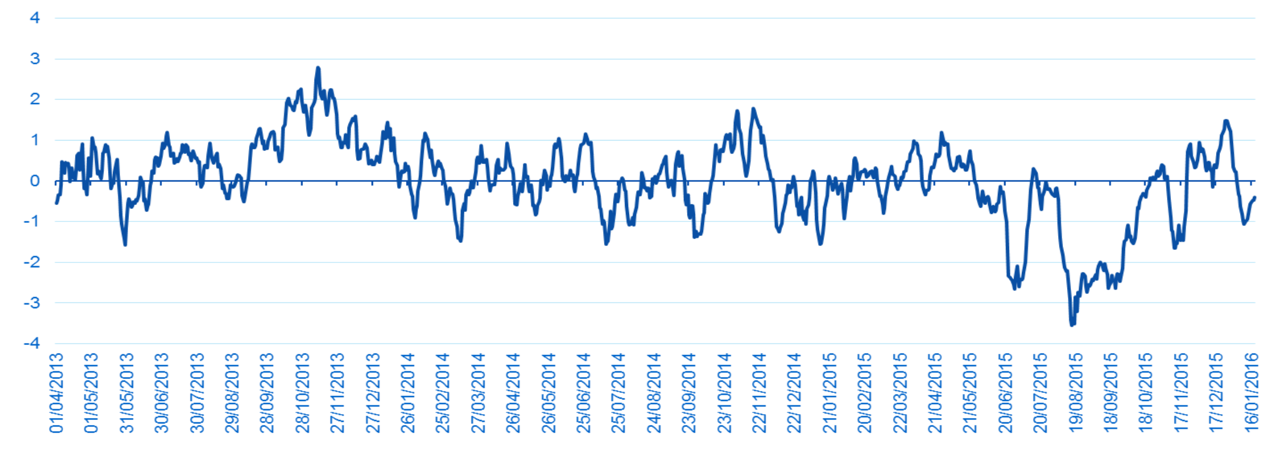
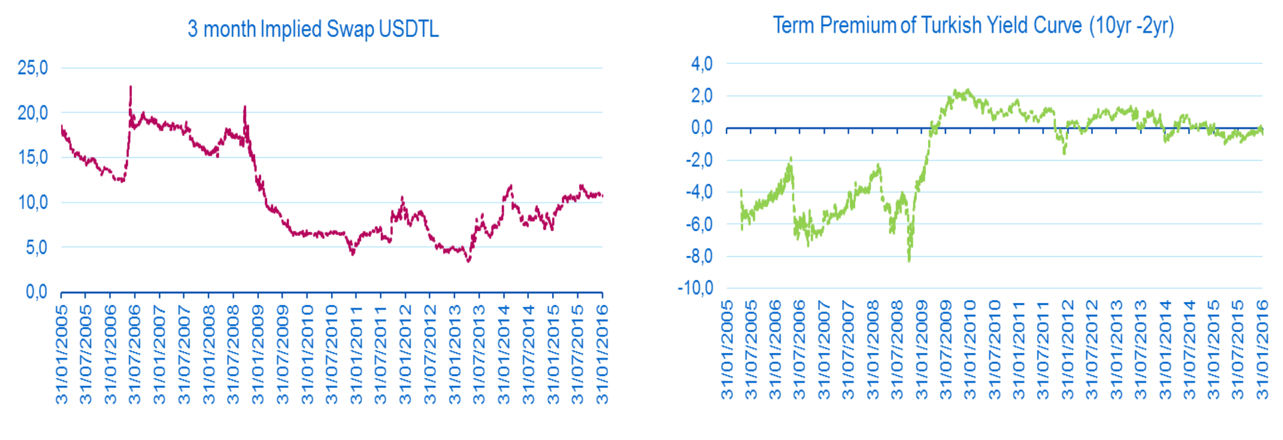
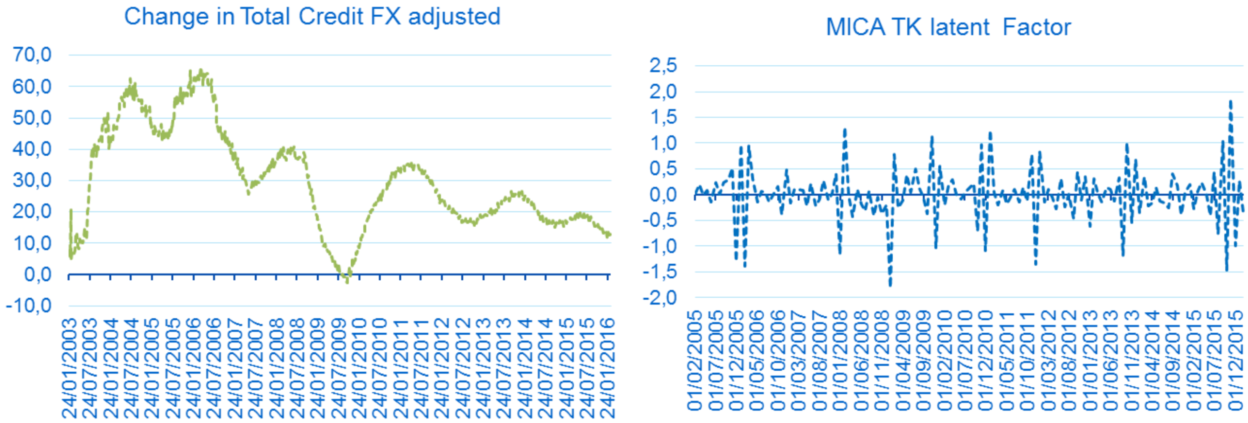


Figure A7
Daily Indicators: Term Premiums and FX swap implied Interest Rates



Source: BBVA Research

Figure A7
Weekly Indicator FX adjusted Credit and Monthly Indicator Industrial Production



Source: BBVA Research

Table 1
Semi out of sample forecasts Root Mean Square Error

Performance Metrics				
	RMSE 1 Step Ahead (2013m4* -2015m9)		Log Likelihood	
Daily Component	GDP| MICA-TK | Credit	MICA-TK monthly	GDP| MICA-TK | Credit	MICA-TK monthly
		0,70		-1873,53
Synthetic UI	0,44	0,47	-1997,36	-1925,53
Monetary UI	0,46	0,48	-1807,25	-1781,25
Politics UI	0,46	0,48	-1792,64	-1756,64
Fiscal UI	0,49	0,47	-1809,51	-1821,51
Global UI	0,49	0,47	-1510,32	-1631,32
Term Premium (10yr-2yr)	0,98	--	-1495,06	--
3 Month Swap USDTL	0,87	--	-1569,28	--

* This is the range where we actually have daily quotes of our uncertanity variable

Source: BBVA Research

Replication files for Aruoba, Diebold and Scotti (2009), "Real-Time Measurement of Business Conditions," Journal of Business and Economic Statistics, vol 27, no 4, 417-427 (RATS)

```
open data
ADS_JBES_PRUEBA_CREDIT+GDELT_SYNTHEX+MICA_v3.xlsx
calendar(7) 1998:01:01
*calendar(7) 1998:1:1
data(format=xlsx,org=columns) 1998:01:01 2016:31:03 ijc1_use
emp1_use $
 gdp1_use slope0_use ijc0_use emp0_use gdp0_use
*
* Get the last observed value for the three non-daily series
*
set ijclast = %if(%valid(ijc0_use{1}),ijc0_use{1},ijclast{1})
set emplast = %if(%valid(emp0_use{1}),emp0_use{1},emplast{1})
set gdplast = %if(%valid(gdp1_use{1}),gdp1_use{1},gdplast{1})
*
* Reset dates for weekly series (Sunday), and quarterly (first date of
* quarter).
*
set resetw  = %weekday(t)==7
set resetq  = %day(t)==1.and.%clock(%month(t),3)==1
*
nonlin b1 b2 b3 b4 g1 g2 g3 g4 rho sig1 sig2 sig3 sig4
*
* Set up the base "C" matrix (author's Z)
*
dec rect c(4,4)
compute c=%zeros(4,4)
compute c(4,1)=1.0
*
* Set up the base "A" matrix (author's T)
*
dec rect a(4,4)
compute a=%zeros(4,4)
*
* Set up the "F" matrix (author's R)
*
dec rect f(4,2)
compute f=%const(0.0)
compute f(1,1)=1.0
compute f(2,1)=1.0
compute f(3,1)=1.0
compute f(4,2)=1.0
*
*****
function DLMSetup
*
* Poke parameters into C array
*
compute c(1,1)=b1
compute c(2,2)=b2
compute c(1,3)=b3
compute c(3,4)=b4
*
* Poke parameters into the A array
*
compute a(1,1)=rho
compute a(2,1)=rho
compute a(3,1)=rho
compute a(4,4)=g1
*
* Set up the SV matrix (author's "H")
compute sv=%diag(||0.0,sig2^2,sig3^2,sig4^2||)
* Set up the SW matrix (author's "Q")
compute sw=%diag(||%if(rho==1.0,1.0,1.0-rho^2),sig1^2||)
end
function DLMPatchA time
type rect DLMPatchA
type integer time
compute a(2,2)=.not.resetw(time)
compute a(3,3)=.not.resetq(time)
compute DLMPatchA=a
end
******
*
* Formula for the observable, subtracting off the AR term for the last 3.
*
dec frml[vect] yf
frml yf = ||slope0_use,ijc0_use-g2*ijclast,emp0_use-
g3*emplast,gdp0_use-g4*gdplast||
*
* The rho value is a borderline unit root. Conditional on one
* observation, the likelihood is maximized with rho=1.
*
compute rho=.95,g1=.90,g2=.90,g3=.90,g4=.90
compute b1=-0.1,b2=-0.1,b3=0.1,b4=0.1
compute sig1=.1,sig2=.1,sig3=.1,sig4=.1
*
* The estimation needs a bit of TLC to prevent it from picking a local
* mode with a negative rho. This pegs the rho at .95 for a small
* number of iterations before freeing rho up.
*
nonlin b1 b2 b3 b4 g1 g2 g3 g4 rho=.95 sig1 sig2 sig3 sig4
dlm(start=DLMSetup(),a=DLMPatchA(t),f=f,sw=sw,presample=ergodic,
$
 c=c,y=yf,sv=sv,$
 pmethod=simplex,piters=10,method=bfgs,iters=20,trace)
nonlin b1 b2 b3 b4 g1 g2 g3 g4 rho sig1 sig2 sig3 sig4
dlm(start=DLMSetup(),a=DLMPatchA(t),f=f,sw=sw,presample=ergodic,
$
 c=c,y=yf,sv=sv,$
 method=bfgs,iters=200,trace)
*nonlin b1 b2 b3 b4 g1 g2 g3 g4 rho=1.00 sig1 sig2 sig3 sig4
*dlm(start=DLMSetup(),a=DLMPatchA(t),f=f,sw=sw,presample=ergodic,
$
*  c=c,y=yf,sv=sv,$
*  method=bfgs,iters=200,trace,condition=1)
*
* Compute smoothed estimates
*
dlm(start=DLMSetup(),a=DLMPatchA(t),f=f,sw=sw,presample=ergodic,
$
 c=c,y=yf,sv=sv,$
 type=smooth) / xstates vstates
*
* Since the sign isn't identified, change the indicator so it goes the
* same way as GDP.
*
{
if b4<0
  set indicator = -%scalar(xstates(t))
else
  set indicator = %scalar(xstates(t))
}
set lower     = indicator-sqrt(%scalar(vstates(t)))
set upper     = indicator+sqrt(%scalar(vstates(t)))
@nbercycles(up=up,down=down)
spgraph(vfields=1,hfields=2)
graph(footer="Smoothed Real Activity Factor Estimation of Q/Q GDP
Growth",shade=down)
# indicator 1999:1:1 2016:01:31
graph(footer="Color Bands are +/- 1 Sigma ",shade=down,min=-
5,max=3) 3
# lower 1999:1:1 2016:01:31 4
# upper 1999:1:1 2016:01:31 2
# indicator 1999:1:1 2016:01:31 1
spgraph(done)
*header="Smoothed Real Activity, QoQ GDP Growth"
```

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