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GREECE MACRO MONITOR

November 18, 2012

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Eurobank GDP NOWcasting model

Greek Q4 GDP forecast: -2.0% QoQ s.a. / -1.9% YoY

Full-year 2013: -3.5% vs. -6.4% last year

Preface

Information about the current state of the real economy is widely dispersed across consumers, firms and policy makers. Individual economic agents may know the recent history of their saving and investment decisions, but they are generally unaware of the contemporaneous decisions of others (Evans 2005). Similarly, policymakers do not have access to accurate contemporaneous information concerning private sector activity. Information about the state of the economy is regularly collected, aggregated and disseminated to the general public by a number of official-sector entities such as national statistic agencies, ministries, employment offices and central banks. Yet, it is generally the case that the collection and aggregation of macroeconomic data takes time and thus, its dissemination (*e.g.* in the form of economic data announcements) occurs with considerable time lags. The implication of this is twofold; first, it inhibits the ability of the monetary (and/or the fiscal) authority to take timely policy decisions that fully incorporate the most recent information on the state of the macroeconomy, and two, it prevent a more accurate understanding of the behavior of private-sector agents and the evolution of asset prices[1]. This paper presents an econometric model that can be used to derive real-time estimates of key macroeconomic variables such as GDP, unemployment and inflation. In the empirical *case study* presented herein, we derive high-frequency estimates of Greek GDP, based on the information provided by a broad range of indicators of domestic economic and market activity.

Real-time inferences

The Nowcasting framework presented in this paper aims to produce high frequency, real-time estimates of Greek GDP by applying an econometric methodology than can properly handle data reporting lags, revisions and other important aspects characterizing the daily flow of macroeconomic information. The econometric model estimated in our study is broadly similar to that initially presented in Evans (2005), with certain modifications being made so as to meet the specific needs of our exercise. In the remaining part of this section we provide a non-technical description of the model and its output, leaving much of the technicalities involved to the Annex section of this document and the initial Evans (2005) paper.

[1] In relation to that point, Evans and Lyons (2004a) demonstrate that the lack of timely information concerning the state of the macroeconomy can significantly influence the dynamics of exchange and interest rates by altering the trading-based process of information aggregation.

As a first step in understanding the structure of this paper it is crucial to highlight and discuss some of the peculiarities characterizing the flow of information that is relevant to the macroeconomy. For this purpose, a distinction needs to be made between the arrival of information and the data collection period (a more formal treatment of this topic is provided in *Appendix I* at the end of this document). Information relevant to the evolution of real economic activity can generally arrive via data releases on any working day (except e.g. national holidays), while GDP data is collected on a quarterly basis. In Greece, the national stats agency, EL.STAT., releases GDP data for any given quarter τ in a sequence of two announcements. These announcements take the form of a *flash* estimate and a *provisional* data release that usually take place in the second and the third month of quarter $\tau+1$, respectively.

Yet, these releases do not actually represent the last official verdict on Gross Domestic Product in quarter τ, as every 1 year or so EL.STAT conducts a comprehensive review of its earlier estimates, an exercise that usually leads to certain revisions in past GDP data. Furthermore, a more comprehensive assessment (and a change of the base year) is conducted every five years. The last such assessment occurred 5 years earlier, leading to a sizeable upward revision of the GDP level, a change of base year to 2005 and a change in the methodology of estimating government expenditure. The latter has effectively created a structural break in the data series in 2008 and thus, quarterly GDP data before and after that year is not directly comparable. That is actually the main reason why EL.STAT does not currently publish quarterly seasonally adjusted data, as the data series after the 2008 revision is not long enough to provide robust seasonally adjusted estimates. Even more frequently than that, revisions to provisional GDP data for quarter τ are included in the GDP data for quarter $\tau+1$.

Following the relevant notation presented in Evans (2005), let us denote by $Q(\tau)$ the last day of quarter τ, by $X_{Q(\tau)}$ the log of real GDP of quarter τ and by $Y_{R(\tau)}$ the *provisional* real GDP growth data released on day $R_Y(\tau)$, which, as we have said earlier, usually falls within the 3rd month of quarter $\tau+1$.

The relation between the provisional GDP growth data and the actual GDP is given by

$$Y_R(\tau) = \Delta^Q X_{Q(\tau)} + U_R(\tau) \qquad (1)$$

Where $\Delta^Q X_Q(\tau) = X_Q(\tau) - X_Q(\tau-1)$ and $U_R(\tau)$ represents the effect of future data revisions i.e., the revision to GDP growth made after $R_Y(\tau)$.

As implied by equation (1) the reporting lag for the provisional quarterly GDP data (i.e., the second report EL.STAT releases on GDP growth of quarter τ) is $R_Y(\tau) - Q(\tau)$. Similarly, the reporting lag for the data series *z* collected during month i of quarter τ is $R_z(\tau,i)-M(\tau,i)$, where $M(\tau,i)$ denotes the last working data of month i and $R_z(\tau,i)$ is the release date of the *z* variable for month i of quarter τ. Reporting lags vary from quarter to quarter and from month to month as data is collected on a calendar basis, while announcements are not made on holidays and weekends (see also Data section of this document).

Finding the real-time estimates at time t of GDP and GDP growth of quarter τ boils down to computing $E[X_{Q(\tau)} / \Omega_t]$ and $E[\Delta^Q X_{Q(\tau)} / \Omega_t]$, where $E[\,.\,/\,.\,]$ denotes conditional expectation and Ω_t is the information set containing all available GDP data and the data for the rest of our macro and market indicators that have been released up to the day t. It is important to note that our Nowcasting model allows us to derive real-time estimates of GDP at any date t, for $t = Q(\tau)$; $Q(\tau) < t \leq Q(\tau+1)$; or $Q(\tau-1) < t < Q(\tau)$.

The estimation process presented in this paper is based on *state-space* framework, where a modified Kalman Filtering algorithm is used to compute maximum likelihood estimates of the model parameters and to produce real time estimates of GDP growth. Although the Kalman Filtering algorithm has been used extensively in the applied time-series literature, its application in the current context has several novel aspects that allow us to deal with the irregularities and the non-synchronized manner of macroeconomic data releases. *Appendix II* at the end of this document provides a more technical treatment of some of the aforementioned issues. For a detailed presentation and analysis on the state-space model used in this study, we refer our reader to the original Evans (2005) paper.

Data

The sources of the data series used to derive real-time estimates of Greek GDP growth include: the Greek statistics agency, EL.STAT, Bank of Greece, the Ministry of Labor, Social Security and Welfare, the Foundation for Economic and Industrial Research (IOBE), ECB and Bloomberg. Data collection and reporting of all series used takes place in monthly frequency, except of real GDP and the retail trade turnover index for which data collection is quarterly. The model is estimating using one quarterly GDP release, which is taken from EL.STAT's Quarterly National Accounts report (provisional data). In our full data sample, the latter report is invariably released in the 3rd month of quarter τ+1 and provided a provisional estimate of real GDP in quarter τ. The other time series used in the model correspond to 24 indicators, which have been selected from an initial set of more than 60 indicators, on the basis of their economic significance and statistical properties. In an interesting deviations from the model presented in Evans (2005), we estimate model specifications which include not only macroeconomic variables such as retail sales, industrial product and unemployment, but also indicators of domestic (and international) market activity, including, the Athens Stock Exchange (ASE) index, the ASE Volatility index, the EONIA rate and the S&P500 implied volatility index, VIX. The selection of these market indicators is made with a view to control for the impact of domestic (and global) market and monetary conditions, especially in periods of increased investor uncertainty. The data samples used herein vary across indicators depending on data availability, with the longest one covering the period from 10 March 2005 to 15 November 2013. The latest period includes 2,139 working days, for the majority of which there were no data releases. For some days there was only one data release and for a much smaller number of days there was more than one release.

Table A1 provides an overview of the data series used to derive real-time estimates of Greek GDP, including relevant information about full-sample periods, data collection periods and reporting frequencies as well as the total number of observations for each series with reporting lags of 0,1,2,3 and 4 months. We note that the data series for the macro indicators used to estimate our model correspond to *initial* data releases *e.g.* before any revisions to past data are made by the corresponding data source/provider. The only exception here concerns the GDP data, for which, as we explained earlier, we use the second release (provisional data) for any given quarter, as there is currently no availability of the time series of initial GDP releases (*flash* estimates). For the market indicators utilized in our study we use end-of-month closing prices/values taken from Bloomberg. We seasonally-adjust the data series used to estimate our model when appropriate (*e.g.* no seasonal adjustment is applied to our market indicators). In line with Evans (2005), we also apply the following data transformation for each of the monthly indicators and the quarterly retail trade turnover index.

Let $z^i_{R(\tau,j)}$ denote the raw value for series i released on day t = R (τ,j), where τ denotes the quarter and j the corresponding month to which the data refers to. The transformed series entering the model has the following semi-differencing form: $z^i_{R(\tau,j)} = (z^i_{R(\tau,j)} - z^i_{mean}) - \alpha_i (z^i_{R(\tau,j-1)} - z^i_{mean})$, where z^i_{mean} is the sample mean of z^i. As noted in Evans (2005), quasi-differencing in this way allows each of the raw-data series to have a differing degree of persistence than the monthly contribution to GDP growth without including serial correlation in the corresponding projection errors. The degree of quasi-differencing depends on the α_i parameters which are jointly estimated with the other model parameters. As a robustness check, we also estimated model specifications which did not incorporate semi-differencing of monthly series in the form described above, but, instead, first differencing of the corresponding series. The results of this exercise are qualitatively similar with the estimates provided by the initial semi-differencing and thus, we do not provide a separate table of results for this case.

Table A1. Data series used in our empirical study

Data series	Source	Full-sample period	Data collection period/ reporting frequency	Number of observations with reporting lag of zero (0) months or quarters	Number of observations with reporting lag of 1 month or quarter	Number of observations with reporting lag of 2 months	Number of observations with reporting lag of 3 months	Number of observations with reporting lag of 4 months
GDP (constant prices)	ELSTAT	3Q 2005-3Q2013	Quarterly	0	35	0	0	0
Retail sales index (volume)	ELSTAT	Mar 2005-Oct 2013	Monhtly	0	0	89	13	0
Road motor vehicles put into circulation for the 1st time	ELSTAT	Mar 2005-Oct 2013	Monhtly	0	98	2	2	0
Unemployment rate	ELSTAT	Apr 2007-Oct 2013	Monhtly	0	0	0	78	0
Number of employeed	ELSTAT	Apr 2007-Oct 2014	Monhtly	0	0	0	78	0
New Primate Sector Hirings	Ministry of Labour, Social Security & Welfare	Jan 2006-Oct 2013	Monhtly	0	92	0	0	0
CPI	ELSTAT	Mar 2005-Oct 2013	Monhtly	0	103	0	0	0
Building permits	ELSTAT	Jan 2008-Oct 2013	Monhtly	0	0	0	67	11
Industrial production index	ELSTAT	Mar 2005-Oct 2013	Monhtly	0	0	102	0	0
Manufacturing production index	ELSTAT	Mar 2005-Oct 2013	Monhtly	0	0	102	0	0
Current account balance	BoG	Mar 2005-Oct 2013	Monhtly	0	0	102	0	0
Turnover index in retail trade	ELSTAT	Jul 2007-Oct 2013	Quarterly	0	0	0	28	1
Index of new orders in industry	ELSTAT	Mar 2006-Oct 2013	Monhtly	0	0	83	2	9
Turnover index in industry	ELSTAT	Oct 2006-Oct 2013	Monhtly	0	0	83	1	0
MFI credit to domestic businesses and households	BoG	Oct 2008-Oct 2013	Monhtly	0	46	13	0	0
Domestic private sector bank deposits	BoG	Mar 2005-Oct 2013	Monhtly	0	101	1	0	0
CPI-based REER	ECB	Mar 2005-Oct 2013	Monhtly	0	102	0	0	0
ULC-based REER	ECB	Mar 2005-Oct 2013	Quarterly	0	0	0	0	35
Central gvnt revenue	FinMin	Mar 2005-Oct 2013	Monhtly	0	102	0	0	0
Central gvnt expenditure	FinMin	Mar 2005-Oct 2015	Monhtly	0	102	0	0	0
Economic Climate Index	IOBE	Mar 2005-Oct 2013	Monhtly	102	0	0	0	0
Athens Stock Exchange (ASE) index	Bloomberg	Mar 2005-Oct 2013	Monhtly	103	0	0	0	0
ASE Volatility	Bloomberg	Mar 2005-Oct 2013	Monhtly	103	0	0	0	0
EONIA	Bloomberg	Mar 2005-Oct 2013	Monhtly	103	0	0	0	0
VIX	Bloomberg	Mar 2005-Oct 2015	Monhtly	103	0	0	0	0

Source: ECB, ELSTAT, EC, Bloomberg, Ministry of Labour, Social Security & Welfare, Eurobank Global Markets Research

Model estimates & analysis

The main essence of our model can be summarized as follows. Each of the macro and market indicators used in our study is first transformed in such as way so as to allow us to account for its degree of relative persistence as regards its contribution in explaining economic growth. Then, each indicator is linked to both its own high-frequency (monthly) releases and to the lower-frequency (quarterly) releases of GDP growth. The latter is assumed to be driven by the combined effect of its own contributions (daily, monthly, and quarterly – *see Appendix II*) and explained by the evolution of various indicators. All component equations of our models are stochastic and contain error terms whose corresponding variances are estimated and reported as log-variance estimates with negative signs (see Table A2). The variance estimates are all significant across models, thus validating the stochastic nature of the equations used. Finally, to model the daily contributions to GDP growth we consider the lagged effects of the monthly announcements and we find that their effect is either very small or statistically insignificant; this means that, during the period of examination, there is little persistence generated at the daily level by the releases and announcements of macroeconomic variables and thus the impact of news dies out rather quickly.

Table A2 below presents the maximum likelihood estimates of: (i) our baseline model, which includes the following variables: GDP (provisional data), economic climate index (ECONCLIMATE) and industrial production index (IP); (ii) an alternative specification including the following variables: GDP (provisional data), economic climate index (ECONCLIMATE), implied ASE volatility (ASEVOL), retail sales volume index (RS) and unemployment rate (UNEMPL); and yet another specification including the following variables: GDP (provisional data), economic climate index (ECONCLIMATE), implied ASE volatility (ASEVOL), retail sales volume index (RS), unemployment rate (UNEMPL), building permits (BUILD), industrial production index (IP), current account balance (CA), industrial orders (ORDERS), private sector bank credit (CREDIT) and number of road motor vehicles put into circulation for 1st time (AUTO). Note that for each specification, the model estimates a great number of parameters. For expositional purposes, Table A2 reports only the parameter estimates that are deemed necessary to facilitate the intuitive understanding of our results.

Additionally to the specifications highlighted above, we estimated a great number of other specifications, with the number of macro and market indicators (besides GDP) ranging from 2 to 24 (i.e., full set of variables presented in Table A1). As a robustness check, we estimated each one of these specifications applying two different data transformation for the monthly indicators used, one with the semi-differencing proposed by Evans (2005) and the other with first differencing of the corresponding series. We also estimated each one of these models with the number of autoregressive terms in the equation specifying the dynamics for the daily contributions, ΔX_t (i.e., the last term of state vector $\mathbf{Z}_t$) ranging from 1 to 4 (see equation (6.4) in Appendix II).

The baseline model in our empirical study is chosen on the basis of a number of diagnostic criteria applied, including significance of coefficients and various goodness-of-fit measures. These criteria unanimously select our baseline specification, which includes the following three variables GDP (provisional data), economic climate index (ECONCLIMATE) and industrial production index (IP). The (real-time) forecast of Greek real GDP growth in Q4 2013 based on the corresponding data released up to 15 November 2013 is as follows: -2.0% quarter-on-quarter seasonally adjusted, which translates into a year-on-year forecast of -1.9% in Q4 and a full-year 2013 forecast of -3.5% vs. -6.4% in 2012. The strong explanatory power of economic climate index found in the majority of estimated model specifications (and the lack of explanatory power of most other macroeconomic and market indicators) is an issue that is examined in greater detail in the next section of this paper.

Table A2 – Model estimates

	Baseline Model *			
	Estimate	Std. error	t value	Pr(> t)
Φ1	0.004	0.009	0.450	0.653
βi coefficient of ECONCLIMATE	0.925	0.326	2.837	0.005
βi coefficient of IP	-0.016	0.287	-0.056	0.955
log-Var(et)	-12.093	0.404	-29.918	0.000
log-Var-ECONCLIMATE	-7.383	0.197	-37.409	0.000
log-Var-ASEVOL	-6.979	0.148	-47.092	0.000

(*) Model variables: ***GDP***, ***ECONCLIMATE*** & ***IP***;

Φ1 is the coefficient of the autoregressive term in equation specifying the dynamics of the daily contributions, ΔX_t - See equation (6.4) in Appendix II); and

β_i is the impact coefficient in in the equation (6.1) of *Appendix II* ($z_t^i = \beta_i \Delta^{M(1)}X_t + u_i^t$) , which projects the monthly indicator z_t^i on $\Delta^{M(i)}X_t$ that denote the monthly contribution to quarterly GDP growth ending on day M(τ, j-i), where M(τ, j) represents the last day of the most recently completed month and t ≥ M(τ,j). Here z_t^i represents the following indicators: *ECONCLIMATE* & *IP* (both indicators enter in quasi-differenced form).

	Alternative Specification I **			
	Estimate	Std. error	t value	Pr(> t)
Φ1	-0.004	0.009	-0.396	0.692
βi coefficient of ECONCLIMATE	0.067	0.255	0.264	0.792
βi coefficient of ASEVOL	-0.806	5.073	-0.159	0.874
βi coefficient of RS	-0.064	0.359	-0.179	0.858
βi coefficient of UNEMPL	-0.058	0.102	-0.567	0.571
log-Var(et)	-11.131	0.663	-16.793	0.000
log-Var-ECONCLIMATE	-7.175	0.154	-46.583	0.000
log-Var-ASEVOL	-3.986	0.226	-17.611	0.000
log-Var-RS	-6.496	0.161	-40.439	0.000
log-Var-UNEMPL	-9.928	0.174	-57.066	0.000

(**) Model variables: ***GDP***, ***ECONCLIMATE***, ***ASEVOL***, ***RS*** & ***UNEMPL***

Φ1 is the coefficient of the autoregressive term in equation specifying the dynamics of the daily contributions, ΔX_t - See equation (6.4) in Appendix II); and

β_i is the impact coefficient in in the equation (6.1) of *Appendix II* ($z_t^i = \beta_i \Delta^{M(1)}X_t + u_i^t$) , which projects the monthly indicator z_t^i on $\Delta^{M(i)}X_t$ that denote the monthly contribution to quarterly GDP growth ending on day M(τ, j-i), where M(τ, j) represents the last day of the most recently completed month and t ≥ M(τ,j). Here z_t^i represents the following indicators: ECONCLIMATE, ASEVOL, RS & UNEMPL (all indicators enter in quasi-differenced form).

Table A2 (continued) - Model estimates

	Alternative Specification II ***			
	Estimate	Std. error	t value	Pr(> t)
Φ1	-0.009	0.002	-3.640	0.000
Φ2	-0.001	0.009	-0.137	0.891
βi coefficient of RS	-0.378	0.496	-0.763	0.446
βi coefficient of AUTO	0.915	1.154	0.792	0.428
βi coefficient of UNEMPL	0.084	0.094	0.894	0.371
βi coefficient of BUILD	-0.141	1.185	-0.119	0.905
βi coefficient of IP	-0.476	0.183	-2.596	0.009
βi coefficient of CA	-0.011	0.035	-0.300	0.765
βi coefficient of ORDERS	-0.107	0.625	-0.171	0.864
βi coefficient of CREDIT	-0.238	0.202	-1.180	0.238
βi coefficient of ECONCLIMATE	0.930	0.546	1.704	0.088
βi coefficient of ASEVOL	0.216	1.635	0.132	0.895
log-Var(et)	-11.516	NA	NA	NA
log-Var-RS	-6.239	0.211	-29.536	0.000
log-Var-AUTO	-3.539	0.190	-18.621	0.000
log-Var-UNEMPL	-9.808	0.258	-37.995	0.000
log-Var-BUILD	-3.255	0.183	-17.832	0.000
log-Var-IP	-7.024	0.228	-30.810	0.000
log-Var-CA	-10.899	1.176	-9.266	0.000
log-Var-ORDER	-5.215	0.241	-21.607	0.000
log-Var-CREDIT	-7.727	0.208	-37.084	0.000
log-Var-ECONCLIMATE	-6.963	0.252	-27.655	0.000
log-Var-ASEVOL	-4.010	0.233	-17.213	0.000

(***) Model variables: ***GDP***, ***ECONCLIMATE***, ***ASEVOL***, ***RS***, ***UNEMPL***, ***BUILD***, ***IP***, ***CA***, ***ORDERS***, ***CREDIT***, ***AUTO***.

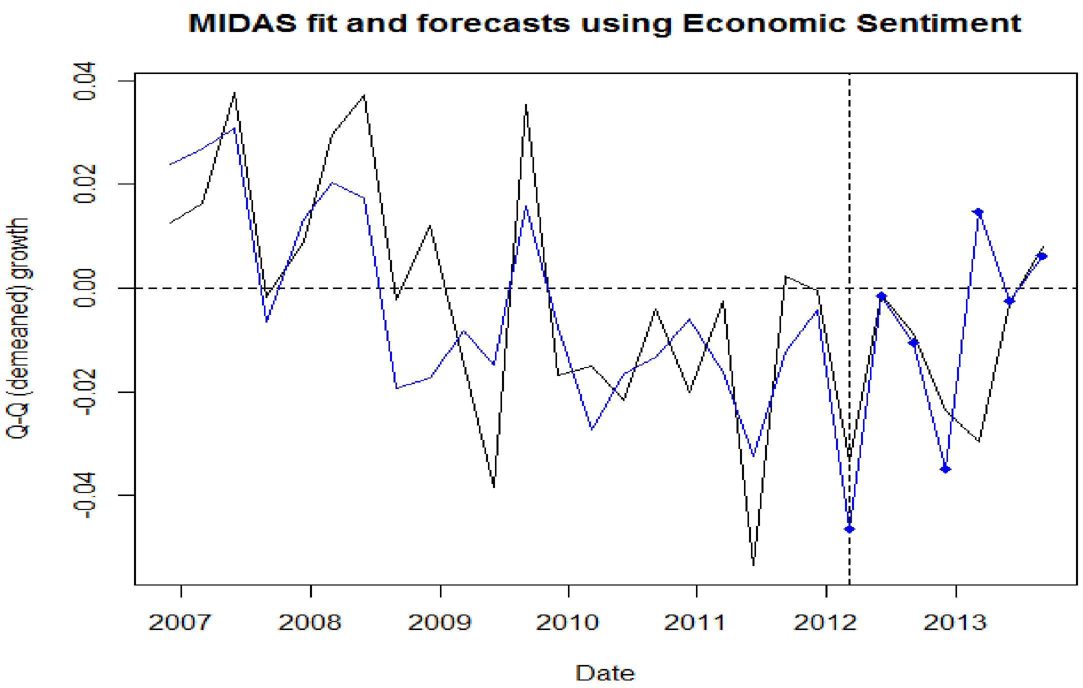
Φ1 and **Φ2** is the coefficient of the autoregressive term in equation specifying the dynamics of the daily contributions, ΔX_t - See equation (6.4) in Appendix II); and

β_i is the impact coefficient in in the equation (6.1) of *Appendix II* ($z_t^i = \beta_i \Delta^{M(1)}X_t + u_i^t$) , which projects the monthly indicator z_t^i on $\Delta^{M(i)}X_t$ that denote the monthly contribution to quarterly GDP growth ending on day M(τ, j-i), where M(τ, j) represents the last day of the most recently completed month and $t \geq M(\tau,j)$. Here z_t^i represents the following indicators: ECONCLIMATE, ASEVOL, RS, UNEMPL, BUILD, IP, CA, ORDERS, CREDIT & AUTO (all indicators enter our model in quasi-differenced form).

Source: Data providers, Eurobank Global Markets Research

Interpreting the importance of the Economic Climate Index in forecasting Greek GDP

How can we interpret the empirical results presented in the previous section and how much weight should be given to the documented statistical significance of the economic climate index? If our results are taken at face value we may then arrive at the conclusion that the economic climate index is indeed a very reliable leading indicator for GDP growth and thus, one could conceivably predict future moves of GDP growth by using this variable alone. To further experiment on the forecasting ability of the economic climate index we apply a completely different methodology than that presented above, which can still handle the unequal frequency of observations (monthly and quarterly) of GDP growth and the economic climate index. More specifically, we apply the MIDAS (Mixed Data Sampling) methodology introduced by Ghysels et al. (2006a, b) to estimate a simple model which links the past evolution of (monthly growth of) the economic climate index and quarterly GDP growth. The model selected is driven by a 9-month maximum delay of the effects of past changes in GDP and the economic climate index. The estimated model not only passes all appropriate diagnostic tests, but also produces quite accurate out-of-sample forecasts. The figure below depicts the results of our experiment, where we leave out the GDP data for 2012 and 2013 (7 observations) so as to produce out-of-sample forecasts. It is interesting to note that with the exception of an overshooting in the first quarter of 2013 the rest of the forecasts track rather well the path of GDP growth. What is important to stress here is that these forecasts are produced using the actual *past* values of GDP growth and economic climate changes and are thus completely valid for inference. While we do not pursue further this exercise at this paper, we note that our results suggests the vital importance of expectations about future economic conditions and support the implementation of policies that can produce and reinforce positive expectations about domestic economic activity. Finally, using our fitted model to produce real-time forecasts for Greek GDP in the 4th quarter of 2013, we find that they suggest an average forecast of seasonally adjusted QoQ growth of -1.8%, with a range of -0.9% to -2.2%, and a potential for positive growth in the first quarter of 2014. (Sources to the figure bellow: MIDAS, Eurobank Global Market Research – Black line corresponds to actual QoQ s.a. GDP growth and blue line to fitted values)

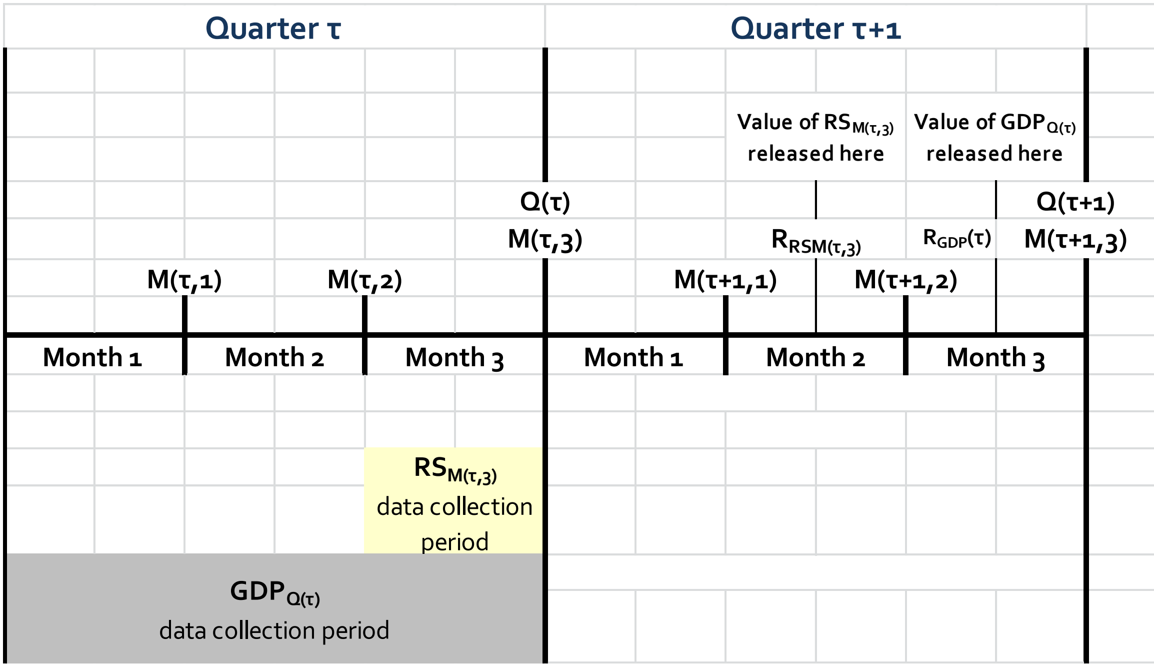


Appendix I

Real-Time Inferences

The Nowcasting framework presented in this paper aims to produce high frequency, real-time estimates of Greek GDP. For this purpose, a distinction needs to be made between the arrival of information and the data collection periods. Information relevant to the evolution of real economic activity can generally arrive via data releases on any working day (except e.g. national holidays), while GDP data is collected on a quarterly basis. Following the relevant notation presented in Evans (2005), we index quarters by τ, with $Q(\tau)$ signifying the last day of quarter τ and $M(\tau, 1)$, $M(\tau, 2)$ and $M(\tau, 3)$ denoting the last days of the first, second and third months of quarter τ, respectively. The day on which a certain data release is taking place is then signified by $R_x(\tau)$ for a quarterly-frequency variable x collected over quarter τ, and by $R_x(\tau,i)$ with i=1,2,3 for a monthly-frequency variable collected over month i of quarter τ. In a similar vein, the value of a quarterly variable x released on day $R_x(\tau)$ is denoted by $x_R(\tau)$, while that of a monthly variable released on day $R_x(\tau,i)$ by $x_R(\tau,i)$. Figure 1 below helps to clarify the aforementioned points, offering a visual depiction of the relationship between data collection periods and reporting lags. The figure portrays the typical data collection periods and release times for Greek Gross Domestic Product and Retail Sales (RS), with $GDP_{Q(\tau)}$ representing real GDP growth in quarter τ and $RS_{M(\tau,3)}$ denoting the value of Greece's retail sales index for the 3rd month of quarter τ.

Figure 1 – Data collection periods & released times for Greek GDP and Retail Sales



Source: Eurobank Global Markets Research

<u>Note to Figure 1</u>

The reporting lags for the initial retail sales and the provisions GDP data depicted in the figure above are $R_{RSM(\tau,3)}$ -$M(\tau,3)$ and $R_{GDP(\tau)}$ - $Q(\tau)$, respectively.

Our analysis of the data series in hand shows that the reporting lag of the retail sales index has been 2 months for the majority of *initial* retail sales data releases. More specifically, in 76 out of a total of 80 such releases, the publication of the retail sales index for a given month (say the 3rd month of quarter τ) has taken place in the second month after the end of the reference quarter (i.e., following the notation presented in Figure 1, in the second month of quarter τ+1).

Greece's statistics agency, EL.STAT, releases GDP data for quarter τ in a sequence of two announcements. As we explained already, these announcements take the form of a *flash* estimate and a *provisional* data release that usually take place in the second and the third month of quarter τ+1, respectively. Yet, these releases do not actually represent the last official verdict on GDP growth in quarter τ as every 5 years EL.STAT conducts a comprehensive review of its earlier estimates, which generally leads to sizeable revisions of past GDP data. Even more frequently than that, revisions to provisional GDP data for quarter τ are included in the GDP data for quarter $\tau+1$.

Again, sticking to the notation presented in Evans (2005), let us denote by $X_Q(\tau)$ the log of real GDP of quarter τ ending on day $Q(\tau)$ and $Y_R(\tau)$ the provisional real GDP growth data released on day $R_Y(\tau)$, which, as we have said earlier, usually falls in the 3rd month of quarter τ. The relation between the provisional GDP growth data and the actual GDP is given by

$$Y_R(\tau) = \Delta^Q X_Q(\tau) + U_R(\tau) \qquad (1)$$

Where $\Delta^Q X_Q(\tau) = X_Q(\tau) - X_Q(\tau-1)$ and $U_R(\tau)$ represents the effect of future data revisions i.e., the revision to GDP growth made after $R_Y(\tau)$. As implied by equation (1) the reporting lag for the provisional quarterly GDP data (i.e., the second report EL.STAT releases on GDP growth of quarter τ) is $R_Y(\tau) - Q(\tau)$. Similarly, the reporting lag for the data series x collected during month i of quarter τ is $R_x(\tau,i)-M(\tau,i)$. Reporting lags vary from quarter to quarter as data is collected on a calendar basis, while announcements are not made on holidays and weekends.

Appendix II

The Model

The real-time estimates of GDP in quarter τ presented in this paper is based on the *provisional* data of Greece's quarterly national accounts (which are regularly reported in the 3rd month of quarter τ+1) and the monthly releases of a range of other macroeconomic and market indicators. For that purpose, we first decompose quarterly GDP growth into a sequence of daily increments as follows:

$$\Delta^Q X_{Q(\tau)} = \sum_{i=1}^{D(\tau)} \Delta^Q X_{Q(\tau-1)+i} \quad (2.1)$$

where $D(\tau) = Q(\tau) - Q(\tau-1)$ is the duration of quarter τ and the daily increment ΔX_t represents the contribution on day t to the growth of GDP in quarter τ. To incorporate then the information contained in the i^th macro variable z^i, we project $z^i_{R(\tau,j)}$ on a portion of GDP growth

$$z^i_{R(\tau,j)} = \beta_i \Delta^M X_{M(\tau,j)} + u^i_{M(\tau,j)} \quad (2.2)$$

Where $\Delta^M X_{M(\tau,j)}$ is the contribution to GDP growth in month j of quarter τ, ($\Delta^M X_{M(\tau,j)} = \sum_{i=M(\tau,j-1)+1}^{M(\tau,j)} \Delta X_i$), β_i is a projection coefficient and $u^i_{M(\tau,j)}$ is a projection error that is orthogonal to $\Delta^M X_{M(\tau,j)}$.

The end-of-quarter real time GDP estimates presented in this paper are then contracted as follows:

$$E[\Delta^Q X_{Q(\tau)} / \Omega_{Q(\tau)}]$$

where $\Omega_t = \Omega^z_t \cup \Omega^y_t$, with Ω^z_t representing the information set comprising of data on the macroeconomic and market indicators used in this study that have been released on or before day t.

The dynamics of the model are characterized by the evolution of the following two partial sums:

$$s^Q_t = \sum_{i=Q(\tau-1)+1}^{\min\{Q(\tau),t\}} \Delta X_i \quad (3.1)$$

$$s^M{}_t = \sum_{i=M(\tau,j-1)+1}^{\min\{M(\tau,j),t\}} \Delta X_i \quad (3.2)$$

Equation (3.1) represents the cumulative daily contribution to GDP growth in quarter τ, ending on day $t \le Q(\tau)$. Similarly, equation (3.2) depicts the cumulative daily contribution to GDP growth between the start of month j in quarter τ and day t, where $t \le M(t,j)$.

To define the daily dynamics of the two partial sums described above, the following dummy variables are introduced:

$\lambda^M_t = 1$ *if* $t = M(\tau,j)+1$, from j = 1,2,3 and zero (0) otherwise.

$\lambda^Q_t = 1$ *if* $t = Q(\tau)+1$, and zero (0) otherwise.

In others words, λ^M_t and λ^Q_t take the value of one if day t is the first day of the month or quarter respectively.

Based on the above definitions, the daily dynamics of s^Q_t and s^M_t can be described by the following equations:

$$s^Q_t = (1-\lambda^Q_t)\, s^Q_{t-1} + \Delta X_t, \quad (4.1)$$

$$s^M_t = (1-\lambda^M_t)\, s^M_t + \Delta X_t. \quad (4.2)$$

The next portion of the model accommodates the reporting lags. Let $\Delta^{Q(j)} X_t$ denote the quarterly growth in GDP ending on day Q(τ-j) where Q(τ) represents the last day of the most recently completed quarter and $t \ge Q(\tau)$.

Quarterly GDP growth in the last (completed) quarter is given by

$$\Delta^{Q(1)} X_t = (1-\lambda^Q_t)\, \Delta^{Q(1)} X_{t-1} + \lambda^Q_t\, s^Q_{t-1} \quad (5.1)$$

When t is the first day of a new quarter, $\lambda^Q_t = 1$ and $\Delta^{Q(1)}X_{Q(t)+1} = s^Q_{Q(t)} = \Delta^Q X_{Q(t)}$. On all other days, $\Delta^{Q(1)}X_t = \Delta^{Q(1)}X_{t-1}$.

Equations (4.1) and (5.1) provide the link between the daily contribution to GDP growth, ΔX_t, and the provisional GDP release, Y_t as follows:

$$Y_t = \Delta^{Q(1)}X_t + U_{R(t)} \tag{5.2}$$

The link between the daily contributions to GDP growth and the monthly macro variables in derived in a similar manner. In more detail, let $\Delta^{M(i)}X_t$ denote the monthly contribution to quarterly GDP growth ending on day M(τ, j-i), where M(τ, j) represents the last day of the most recently completed month and t ≥ M(τ,j). The contribution το GDP growth in the last (completed) month is the given by

$$\Delta^{M(i)}X_t = (1-\lambda^M_t)\,\Delta^{M(i)}X_t + \lambda^M_t\,\Delta^{M(i-1)}X_{t-1}. \tag{5.3}$$

Similarly to the case above, if t is the first day of a new month, $\lambda^M_t = 1$, then $\Delta^{M(1)}X_{M(\tau,j)+1} = s^Q_{M(\tau,j)} = \Delta^M X_{M(\tau,j)}$ and $\Delta^{M(i)}X_{M(\tau,j)+1} = \Delta^{M(i-1)}X_{M(\tau,j)+1}$ for J = 1,2,3. On all other days, $\Delta^{M(i)}X_t = \Delta^{M(i)}X_{t-1}$.

The $\Delta^{M(i)}X_t$ variables link the monthly data releases, z^i, to quarterly GDP growth as follows:

If the reporting lag for macro series i is less than one month, the value released on day t can be written as

$$z_t^i = \beta_i \Delta^{M(1)}X_t + u_i^t. \tag{6.1}$$

If now the reporting lag for the variable z^i is two months, the value released on day t can be written

$$z_t^i = \beta_i \Delta^{M(2)}X_t + u_i^t. \tag{6.2}$$

The same concept applies to data releases with reporting lags of three or more months, while for macro series with reporting lags of zero months (i.e., release takes place before the end of reference month), equations (6.1) and (6.2) take the following form:

$$z_t^i = \beta_i s_M^t + u_i^t. \tag{6.3}$$

To complete the model we next specify the dynamics for the daily contributions, ΔX_t as follows:

$\Delta X_t = \sum_{i=1}^{k} \varphi_i \Delta^{M(1)}X_t + e_t$, where e_t is an i.i.d., zero mean normally-distributed shock with variable σ^2_e (6.4)

Note that the last equation expresses the growth contribution on day t as a weighted average of the monthly contributions over the last k (completed) months, plus an error term.

Finding the real time estimates of GDP and GDP growth boils down to computing $E[X_{Q(t)} / \Omega_t]$ and $E[\Delta^Q X_{Q(t)} / \Omega_t]$ using the quarterly signaling equation (5.2), the monthly signaling equations (6.1)-(6.3) and the ΔX_t process specified in equation (6.4) given the values of all estimated parameters in these equations. This estimation process is complicated by the fact that individual data releases are irregularly spaced, and arrive in a non-syncronized manner: On some days there may be only one release, on others there are several, and on some there are none at all. In short, the temporal pattern of data releases is quite unlike that found in standard time-series applications. The Kalman Filtering algorithm provides a solution to both problems. In particular, given a set of parameter values, the algorithm provides the means to compute the real-time estimates $E[X_{Q(t)} / \Omega_t]$ and $E[\Delta^Q X_{Q(t)} / \Omega_t]$. The algorithm also allows us to construct a sample likelihood function from the data series, so that the model parameters can be computed by maximum likelihood. Although the Kalman Filtering algorithm has been used extensively in the applied time-series literature, its application in the current context has several novel aspects that are properly dealt with in the framework provided in Evans (2005).

In what follows, we provide a brief description of the state-space form we use to write the model so as to generate the aforementioned calculations.

Starting with the state equation, this can be represented as follows:

$$Z_t = A_t Z_{t-1} + V_t \tag{7}$$

where, in our case, Z_t is the following 9x1 vector

$Z_t = [s^Q_t, \Delta^{Q(1)}X_t, s^M_t, \Delta^{M(1)}X_t, \Delta^{M(2)}X_t, \Delta^{M(3)}X_t, \Delta^{M(4)}X_t, \Delta^{M(5)}X_t, \Delta X_t]'$ and

A_t is a 9x9 coefficient matrix constructed by equations (4.1), (5.1) and (6.1)-(6.4).

We note here that the dimension (and the elements) of state vector Z_t in our model are determined by the release lags of the quarterly and monthly data we use. These are: 1 quarter for GDP (and a couple of other quarterly-frequency indicators we use); and 0 to 5 months for the monthly indicators. Finally, for the autoregressive parameter φ_i used to describe the dynamics of the daily contribution, ΔX_t, in equation (6.4), we estimate (as a test for robustness) different specifications with k = 0,1,2 & 3. Furthermore, unlike to traditional state space specifications, the state transition matrix A_t is not constant but depends on the values of quarterly and monthly dummies λ^M_t an λ^Q_t and thus, it is time-varying.

We next turn to the observation equation, which has the following form:

$$X_t = C_t Z_t + U_t \qquad (8)$$

where X_t is the vector of *potential* data releases for day t, Z_t is the state vector and C_t the corresponding coefficient matrix.

Here, $X_t = [\, Y_t, z^1_t, z^2_t, \ldots z^j_t]'$ is a λx1 vector, where, as we noted earlier, Y_t represents the provisional GDP and $z^1_t, z^2_t, \ldots z^j_t$ are the monthly indicators utilized in our study. C_t is a λx9 matrix, with its first row having the following form:

[0, 1, 0, 0, 0, 0, 0, 0, 0]′, since in our data sample provisional GDP data for quarter τ is always released before the end of quarter τ+1,

and its following λ-1 rows being represented as follows:

$[0, 0, \beta_J ML^0_t(z^j), \beta_J ML^1_t(z^j), \beta_J ML^2_t(z^j), \beta_J ML^3_t(z^j), \beta_J ML^4_t(z_j), \beta_J ML^5_t(z_j), 0]'$, for row J of matrix C_t,

where $ML^m_t(z^j)$, is a dummy variable that takes the value of 1 when the z^j macro/market indicators for a certain month of quarter τ is released with a time lag of m months (in our data sample, m=0,1,2,3,4 &5).

Again, equation (8) links the vector of potential data releases for day t, X_t, to the elements of the state vector, Z_t. The elements of X_t identify the value that would have been released for each series given the current state, Z_t; if day t was in fact the release day. Of course, on a typical day, we would only observe the elements in X_t that correspond to the actual releases that day. For example, if data on provisional GDP and monthly series i = 2 & 3 were released on day t, we would only observe the values in the 1st, 3rd, and 4th rows of X_t. On the other hand, on days when there are no releases, none of the elements of X_t are observed.

The vector of actual data releases for day t, Y_t, is related to the vector of potential releases by the following equation:

$$Y_t = B_t X_t \qquad (8.1)$$

where B_t is a nx9 selection matrix that "picks out" .the n ≥1 data releases for day t.

Combining equations (8) and (8.1) gives the observation equation:

$$Y_t = B_t C_t Z_t + B_t U_t \qquad (8.2)$$

Equation (82) differs in several respects from the observation equation specification found in standard time-series applications. First, the equation only applies on days for which at least one data release takes place. Second, the link between the observed data releases and the state vector varies through time via C_t as $QL^i_t(z)$ and $ML^i_t(z)$ change. These variations arise because the reporting lag associated with a given data series change from release to release. Third, the number and nature of the data releases varies from day to day (i.e., the dimension of Y_t can vary across consecutive data-release days) via the B_t matrix.

Equations (7) and (8) describe a state space form which can be used to derive real-time estimates of GDP. The estimation takes place in two steps. First, the maximum likelihood estimates of the model parameters are derived. Second, real-time estimates of GDP are calculated using the maximum likelihood parameter estimates from the first step. A more thorough analysis of these steps is provided in Evans (2005).

Derivation of Real-Time estimates of GDP

Upon deriving the maximum likelihood estimates of the model parameters, the Kalman Filtering equations can be used to derive real-time estimates of Greek GDP. These are given by the following formulas:

Real-time estimates of quarterly GDP growth in quarter τ

For **t = Q(τ)** *i.e.*, the last day of the reference quarter, real GDP growth of quarter τ estimated based on the information (i.e., values of the data series used) available at day t is given by

$$\Delta^Q X_{Q(\tau)/Q(\tau)} = E\,[s^Q_{Q(\tau)} / \Omega_{Q(\tau)}] = h_1 Z^{est}_{Q(\tau)/Q(\tau)}$$

where h_1 is a selection indicator that selects the first row of the 9x1 vector estimate Z at time t= Q(τ)

For **Q(τ) < t ≤ Q(τ+1)** *i.e.*, for days falling in quarter τ+1, real GDP growth of quarter τ estimated based on the information (i.e., values of the data series used) available at day t is given by

$$\Delta^Q X_{Q(\tau)/t} = h_2 Z^{est}_{t/t}$$

where h_2 a the selection indicator that selects the second row of the 9x1 vector estimate Z at time t

For **Q(τ-1) < t < Q(τ)** *i.e.*, for days after the first (and before the last) day of quarter τ, real GDP growth of quarter τ estimated based on the information (i.e., values of the data series used) available at day t is given by

$$\Delta^Q X_{Q(\tau)/t} = [h_1 + h_4\, \varphi^{est}\, (Q(\tau)\text{-}t)\}\, Z^{est}_{t/t}$$

when there is only one autoregressive parameter (k=1) in the specification of the dynamics for the daily contributions, ΔX_t, (i.e., the last element of the state vector Z). Here h_1 and h_4 are selection indicators that select the first and fourth elements of the 9x1 vector estimate Z at time t.

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