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## **A real-time measure of business conditions in Malta**

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## **Abstract**

This paper outlines the structure for a high frequency measure of economic activity in Malta, with the ability of identifying turning points and changes in activity in real time. An array of flow and stock data is applied, measured at mixed frequencies. A dynamic factor model then filters the data and constructs a high frequency business conditions index (BCI). The framework is based on a study by Aruoba, Diebold and Scotti (2009). In this paper, their prototype example is extended to include extra monthly variables.

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## Table of Contents

Abstract.....	2
1. Introduction.....	4
2. Data.....	6
3. The model.....	8
3.1 State-space representation.....	8
3.2 Implementing the model .....	9
4. Results.....	11
4.1 Turning-point analysis.....	12
4.2 BCI and the output gap.....	14
4.3 BCI and the European Commission's business climate indicator .....	16
5. Conclusion.....	17
6. References .....	18
7. Appendix 1: Stability .....	19

## 1. Introduction and literature review

Policymakers have to make decisions based on the best set of economic information available at that particular point in time. This information will describe the health and pace with which different sectors, or the economy in general, are evolving over time. Ideally, real-time analysis of short-term developments in the economy - carried out to assess the true state of the economy at the current point in time - would incorporate a fully updated information set. In the real world, however, there are a number of challenges to be faced. Decision makers do not always have access to timely economic data. Many variables tend to be unavailable at times when they are most at need. For example, high-frequency gross domestic product (GDP) data is unavailable for Malta. Additionally, national accounts figures describing Maltese growth tend to be published with a notable lag from their reference period.

Moreover, additional variables which provide key pieces of information to understand the overall position of the economy are updated asynchronously or with further delays. Unfortunately, this means that recently published data may end up being irrelevant for 'current' policymaking or business investment decisions, as it tends to refer to periods which have long since passed. Economic integration and co-dependence, global competition and instant spillover effects require fast-paced decisions. If local decision making is to be prepared for, and take advantage of such shifts then macroeconomic analysis of the local economy ought to be improved.

Understanding changes in the pace of economic activity also gained importance in macroeconomic analysis over recent years due to the poor performance of existing models in predicting recessions. Due to the considerable impact of business cycles on economic fluctuations, forecasting turning points in business cycles is another crucial step in economic decision making. A business cycle measure would indicate the current state of economic conditions and, crucially, their direction over time.

A measure of aggregate business conditions acts as a useful aid to assess the direction of economic activity, and it serves as a useful input in analysing current economic performance. In effect, a well specified business conditions index acts as a summary statistic of the economy's health at a point in time.

The importance of providing a current indication of the state of the economy led to a large volume of research into coincident indicators of business-cycles and economic activity. Following Stock and Watson (1989), indices of coincident and leading economic indicators using a single dynamic factor approach induced further applications and parallel research in the area. Significant and notable contributions in developing and refining methodologies to compute economic activity and business cycle indicators were made, such as Altissimo et al (2001), Giannone, Reichlin, and Small (2006), Angelini, Bańbura, and Rünstler (2008), Aruoba, Diebold and Scotti (2009), Camacho and Pérez-Quirós (2008), and Mariano and Murasawa (2010).

Some of this research in business conditions indices appears to favour a very large number of variables, with economic activity seen to be reflected in the co-movements between as many variables as possible. Other empirical and academic research follows the notion that smaller models in general, and more specifically the careful selection of a parsimonious number of indicator variables, will lead to accurate estimates. Many coincident indices are computed for various economies or industries, with a wide heterogeneity in specifications and variable selection - particularly those models based on a restricted pool of variables. Coincident indicators are constructed for the euro area, the United States, Italy, Spain and various other countries.

This paper presents a simple business condition index calculated for Malta, based upon Aruoba, Diebold and Scotti (2009).<sup>1</sup> This framework is seen to respect four key principles, and provides a high-frequency assessment of business conditions.

- This approach uses a dynamic factor model, which treats business conditions as an unobserved variable, which is related to observed indicators. Business cycles are latent, in line with Lucas (1976), in that they are not related to the evolution of any single variable – but conditioned by dynamics and co-movements between many variables.
- The ADS (2009) approach incorporates business conditions indicators measured at different frequencies. This recognises the fact that indicators are indeed published at different frequencies. For example, GDP is published in quarterly frequency, indicators related to industrial production are published monthly, while most financial variables are measured on a daily basis. A measure that successfully incorporates all of them will provide a continuously updated indication on the direction and health of the Maltese economy.
- Additionally, this method intentionally incorporates indicators measured at high frequencies. While sourcing such variables in Malta is problematic, it is crucial to incorporate as much high-frequency information as possible. Unfortunately, the inability to identify weekly variables as used in the original paper led to the changing of the modelling framework to consider monthly variables; however, the paper’s use of the daily term-structure of interest rates as the daily backbone of the model was retained.
- Finally, latent business conditions are extracted and forecasted using linear – but statistically optimal – procedures. These do not use approximations.

In line with the original paper, this study takes a small data approach to dynamic factor analysis of business conditions. It recognises the importance of using mixed-frequency data and high-frequency data, it handles the innate problems with filtering missing data using a Kalman filter. It also provides a prototype index of business conditions in Malta.

Another challenge faced in an analysis of turning points in economic activity and business cycles in Malta is the lack of official business cycle dating of the Maltese economy. In that respect, this paper presents the results from the modified Bry and Boschan (1971) quarterly algorithm, based on a routine made available by NCER.<sup>2</sup> Empirically tested turning points will allow for a meaningful analysis of the BCI’s ability to capture movements in the Maltese economy.

The paper is structured as follows. The next section discusses the data and the variables used in the model. *Section 3* focuses on the model, its state space representation, signal extraction and implementation. *Section 4* discusses the results, comparing particular events with empirical turning points of the Maltese economy. The way forward and a conclusion are found in *Section 5*. An appendix briefly discusses model stability.

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<sup>1</sup>Henceforth referred to as ADS (2009).

<sup>2</sup>The National Centre for Econometric Research (NCER) in Australia was founded by the QUT Business School in 2006. Various routines to date business cycles are publicly available within the Centre’s repository. The codes provided by Sam Ouliaris at the International Monetary Fund were used to date the Maltese business cycle.

## 2. Data<sup>3</sup>

Starting from high to low-frequency, the first variable is the term structure of local interest rates. This variable refers to the relationship between interest rates or yields measured over different terms, or maturities. The term structure of interest rates is also referred to as the yield curve, and it plays a pivotal role in an economy. The definition used in this paper is the difference between the offer rate for the ten-year benchmark bond yield for Malta (ISMA definition), and the offer rate on the secondary-market for the three-month Treasury bill. Thus, it can be called the ‘term premium.’

The study uses six variables measured at a monthly frequency. Three of these are published by the National Statistics Office. These are industrial production, taxation revenues for general government (cash definition) and registered unemployment.<sup>4</sup> These are treated as a flow variable.

Additionally, this study uses a variable published by the Malta International Airport, namely the airline seat-capacity serving Malta. This variable is closely tied to the tourism sector, and can also be seen to proxy developments in the services industry in general. Seat-capacity sums the total available seats available in flights operated by all airline companies landing at the Malta International Airport in any given month. This index provides a key insight into the workings of the local tourist industry, as well as serves as a proxy for how well-linked the Maltese islands are with the rest of the world.<sup>5</sup>

A credit variable is also included, namely the provision of credit to households for mortgages, along with the European Commission’s (EC) economic sentiment indicator (ESI). Finally, the index also features chain-linked GDP volumes. As the model is specified in quarter-on-quarter growth rates, all the variables - except for the term premium - are seasonally adjusted and considered in logarithmic differences.

This is due to the distinctive seasonal pattern in local variables, due to the influx of tourists in the summer months. Seasonally adjusted data is obtained from X-12 seasonal adjustment using *IHS®-EViews®* software. The quarter-on-quarter specification is a sufficient condition for seasonal adjustment, with most macroeconomic indicators returning a seasonal pattern. Seasonal adjustment is seen as an important step to remove most of the non-informative dynamics in local variables. For example, there is a marked difference between seasonally adjusted and unadjusted GDP growth rates (see *Figure 1*).

The business climate indicator published by the EC is excluded from the approach, in order to allow the benchmarking of the model’s results against an independent estimate of business conditions.

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<sup>3</sup>The cut-off point for GDP data is the national accounts 2015Q4 GDP release. All other variables are updated up to the first week of March 2016. An evaluation using ‘live’ data vintages is included in the Appendix.

<sup>4</sup>For the final specification of the business conditions index, the ‘registered unemployment’ variable was modelled as a three-month moving average. While counterintuitive in the context of a coincident indicator of the local economy, this transformation was deemed necessary to account for a marked decrease in registered unemployment - in evidence since following the first quarter of 2014. This is possibly the result of an administrative change in measurement, rather than a change brought about by underlying economic activity. This position will be reviewed once more is known on the nature of this development.

<sup>5</sup>Implicitly, the assumption behind the use of this variable rather than for example, the seat load-factor, is that airline companies will cancel routes to Malta as soon as they are deemed unprofitable. This is not seen to be a restrictive assumption.

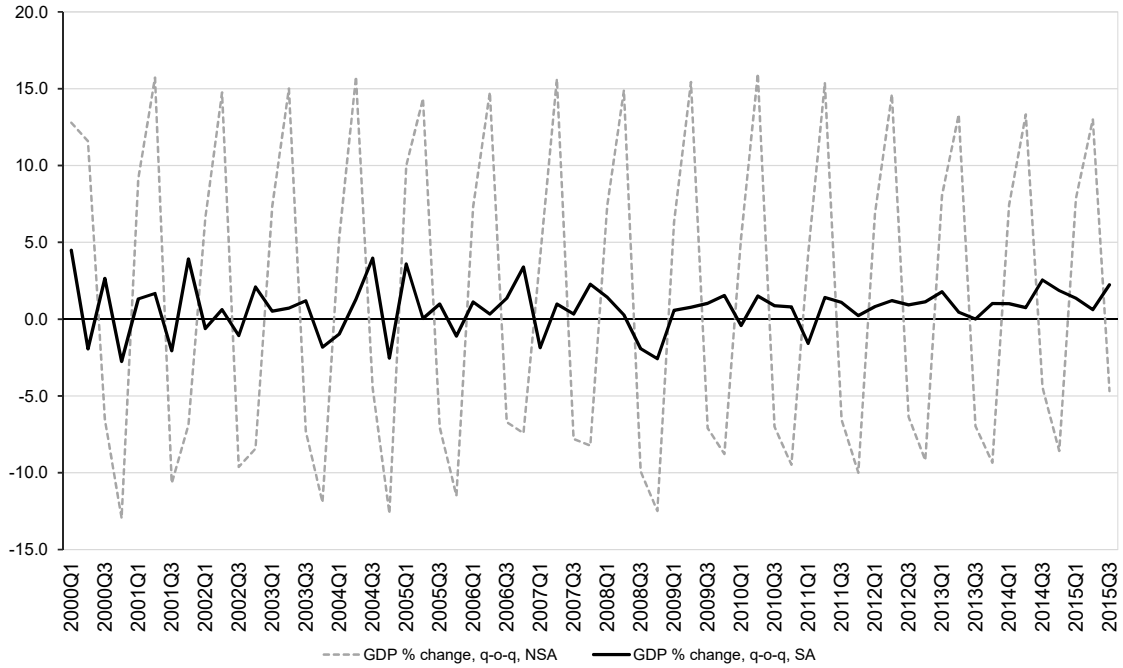


Figure 1: Gross domestic product (GDP) growth in Malta, quarter-on-quarter (q-o-q)

The idea behind a business conditions index is to use data as it becomes available from various sources. This is then used to update an estimate of the overall level of economic activity and the direction of the economy. This index takes the view that there is some underlying “daily” level of economic activity, with the status evolving progressively over time. The basic idea behind the specification in this paper is that given the previous indication of where the economy appeared to be when the data was updated last, and given the slowly changing dynamics behind economic activity, one will be able to arrive to a prediction for what the next available value of the indicator will show.

Thus when the model is updated with newly published data, and this data is more favourable than projected, then the inferred level of average economic activity will be revised slightly upward. If the published data is less favourable, the implied index for economic activity is then revised slightly downward. The basis of this signal extraction is a simple Kalman filter.

### 3. The model

#### 3.1. State space representation

The model can be defined in state space representation, which allows a simple discussion on filtering and estimation. Following ADS (2009), cast in state space form, the model can be defined simply as:

$$y_t = Z_t \alpha_t + \Gamma_t w_t + \varepsilon_t \quad (1)$$

$$\alpha_{t+1} = T \alpha_t + R \eta_t \quad (2)$$

$$\varepsilon_t \sim (0, H_t), \eta_t \sim (0, Q) \quad (3)$$

$$t = 1, \dots, \tau,$$

where  $y_t$  is an  $N \times 1$  vector of observed variables, with missing observations due to frequency constraints.  $\alpha_t$  is an  $m \times 1$  vector of state variables,  $w_t$  is an  $e \times 1$  vector of predetermined variables with a constant term (in unity),  $k$  trend terms and  $N \times n$  lagged dependent variables ( $n$  for each of the  $N$  elements in the  $y_t$  vector),  $\varepsilon_t$  and  $\eta_t$  are vectors of measurement and transition shocks comprising the respective  $u_t^i$  and  $e_t$ , with  $\tau$  standing for the final time-series observation.

In practice, the vector  $y_t$  containing the observables will have a large number of missing observations. Daily data will be missing due to holidays or weekends, while variables published only monthly or every three months are going to be observed at comparatively fewer points than a daily variable. The missing data, however, do not cause large problems to this framework, as a Kalman filter will remain valid.

##### 3.1.1. Signal extraction

The Kalman filter and its smoother are used to obtain optimal extractions of the latent state of real activity in the economy. The Kalman filter is initialised using the unconditional mean and covariance matrix of the state vector. The contemporaneous Kalman filter, following Durbin and Koopman (2001) is used.

Letting  $Y_t \equiv \{y_1, \dots, y_t\}$ ,  $a_{t|t} \equiv E(\alpha_t | Y_t)$ ,  $P_{t|t} \equiv \text{var}(\alpha_t | Y_t)$ ,  $a_t \equiv E(\alpha_t | Y_{t-1})$ , and  $P_t \equiv \text{var}(\alpha_t | Y_{t-1})$ , then the Kalman filter updating and prediction equations will be:

$$a_{t|t} = a_t + P_t Z_t' F_t^{-1} v_t$$

$$P_{t|t} = P_t - P_t Z_t' F_t^{-1} Z_t P_t'$$

$$a_{t+1} = T a_{t|t}$$



$$P_{t+1} = TP_tT' + RQR'$$

where:

$$v_t = y_t - Z_t a_t - \Gamma_t w_t$$

$$F_t = Z_t P_t Z_t' + H_t$$

for  $t = 1, \dots, \tau$ .

Fundamental to this approach is the fact that the Kalman filter remains valid even if there are missing data. If all elements in  $y_t$  are missing, the updating process is skipped and the recursion simply becomes:

$$y_t^* = Z_t^* \alpha_t + \Gamma_t^* w_t + \varepsilon_t^*$$

$$\varepsilon_t^* \sim N(0, H_t^*)$$

where  $y_t^*$  is of dimension  $N^* < N$ , containing the observed elements of the  $y_t$  vector. The key to the Kalman filter under these conditions is that  $y_t^*$  and  $y_t$  are linked with the transformation  $y_t^* = W_t y_t$ , where  $W_t$  is a matrix whose  $N^*$  rows will be the rows of  $I_N$  which correspond to the elements of  $y_t$  which are actually observed. Similarly,  $Z_t^* = W_t Z_t$ ,  $\Gamma_t^* = W_t \Gamma_t$ ,  $\varepsilon_t^* = W_t \varepsilon_t$ , and  $H_t^* = W_t H_t W_t'$ . The Kalman filter will work as described above, replacing  $y_t$ ,  $Z_t$  and  $H$  with  $y_t^*$ ,  $Z_t^*$  and  $H_t^*$ . Likewise, the Kalman smoother continues to be valid with missing data following the same transformation.

### 3.2. Implementing the model

The model used in this paper follows the prototype model presented in ADS (2009). A detailed discussion on the modeling framework, on the specification of the dynamic factor model at daily frequency, treatment of aggregations and trends, as well as further details on the model's state space representation, signal extraction and estimation can be found in the original paper. The prototype discussed in the paper is derived following two simplifying assumptions which reduced the number of parameters that had to be estimated using numerical likelihood optimisation. First, the data are detrended prior to starting fitting the model, rather than estimating trend parameters at the same time as the others, and, secondly, simple first order dynamics are used throughout.

Latent business conditions  $x_t$  are assumed to follow a zero-mean AR(1) process, as do the other variables observed at their respective frequencies. For monthly industrial production, unemployment, seat-capacity, mortgage credit, taxation revenues, the ESI and quarterly GDP, this simply means that the lagged values of these variables are elements within the  $w_t$  vector. These are denoted by  $\tilde{y}_{t-M}^2, \tilde{y}_{t-M}^3, \tilde{y}_{t-M}^4, \tilde{y}_{t-M}^5, \tilde{y}_{t-M}^6, \tilde{y}_{t-M}^7, \tilde{y}_{t-q}^8$ , where  $M$  denotes the number of days in a month and  $q$  denotes the number of days in a quarter.<sup>6</sup>

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<sup>6</sup>For the sake of simplicity, the notation in the paper assumes  $M$  and  $q$  are constant over time. In the implementation, however, these are adjusted according to the number of days in the actual month or quarter.

For the term premium,  $\tilde{y}_t^1$ , the autocorrelation structure is modelled as an AR(1) process for the measurement equation innovation,  $u_t^1$ , instead of adding a lag of the term premium in  $w_t$ .

$$\underbrace{\begin{bmatrix} \tilde{y}_t^1 \\ \tilde{y}_t^2 \\ \tilde{y}_t^3 \\ \tilde{y}_t^4 \\ \tilde{y}_t^5 \\ \tilde{y}_t^6 \\ \tilde{y}_t^7 \\ \tilde{y}_t^8 \end{bmatrix}}_{y_t} = \underbrace{\begin{bmatrix} \beta_1 & \beta_2 & \beta_3 & \beta_4 & \beta_5 & \beta_6 & \beta_7 & \beta_8 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \beta_8 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \beta_8 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \beta_8 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \beta_8 \text{ or } 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \beta_8 \text{ or } 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \beta_8 \text{ or } 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & \beta_8 \text{ or } 0 \end{bmatrix}}_{Z_t} \underbrace{\begin{bmatrix} x_t \\ x_{t-1} \\ \vdots \\ x_{t-\bar{q}-1} \\ x_{t-\bar{q}} \\ u_t^1 \end{bmatrix}}_{\alpha_t} + [\dots]$$

$$[\dots] + \underbrace{\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma_2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \gamma_3 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \gamma_4 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \gamma_5 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \gamma_6 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \gamma_7 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \gamma_8 \end{bmatrix}}_{\Gamma_t} \underbrace{\begin{bmatrix} \tilde{y}_{t-M}^2 \\ \tilde{y}_{t-M}^3 \\ \tilde{y}_{t-M}^4 \\ \tilde{y}_{t-M}^5 \\ \tilde{y}_{t-M}^6 \\ \tilde{y}_{t-M}^7 \\ \tilde{y}_{t-M}^8 \\ \tilde{y}_{t-q}^8 \end{bmatrix}}_{w_t} + \underbrace{\begin{bmatrix} 0 \\ u_t^{*2} \\ u_t^{*3} \\ u_t^{*4} \\ u_t^{*5} \\ u_t^{*6} \\ u_t^{*7} \\ u_t^{*8} \end{bmatrix}}_{\epsilon_t}$$

$$\underbrace{\begin{bmatrix} x_{t+1} \\ x_t \\ \vdots \\ x_{t-\bar{q}} \\ x_{t-\bar{q}+1} \\ u_{t+1}^1 \end{bmatrix}}_{\alpha_{t+1}} = \underbrace{\begin{bmatrix} \rho & 0 & \dots & 0 & 0 & 0 \\ 1 & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & \dots & 1 & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 & \gamma_1 \end{bmatrix}}_T \underbrace{\begin{bmatrix} x_t \\ x_{t-1} \\ \vdots \\ x_{t-\bar{q}-1} \\ x_{t-\bar{q}} \\ u_t^1 \end{bmatrix}}_{\alpha_t} + \underbrace{\begin{bmatrix} 1 & 0 \\ 0 & 0 \\ \vdots & \vdots \\ 0 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix}}_R \underbrace{\begin{bmatrix} e_t \\ \zeta_t \end{bmatrix}}_{\eta_t}$$

$$\begin{bmatrix} \varepsilon_t \\ \eta_t \end{bmatrix} \sim N \left( \begin{bmatrix} 0_{8 \times 1} \\ 0_{2 \times 1} \end{bmatrix}, \begin{bmatrix} H_t & 0 \\ 0 & Q \end{bmatrix} \right), \quad H_t = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{2t}^{*2} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_{3t}^{*2} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{4t}^{*2} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{5t}^{*2} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_{6t}^{*2} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma_{7t}^{*2} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma_{8t}^{*2} \end{bmatrix}, \quad Q = \begin{bmatrix} 1 & 0 \\ 0 & \sigma_1^2 \end{bmatrix}$$

The notation above follows that found in the ADS (2009) paper, but the model itself was changed to better suit Maltese data limitations. A weekly variable was dropped, while further monthly variables were added in the modelling framework.

## 4. Results

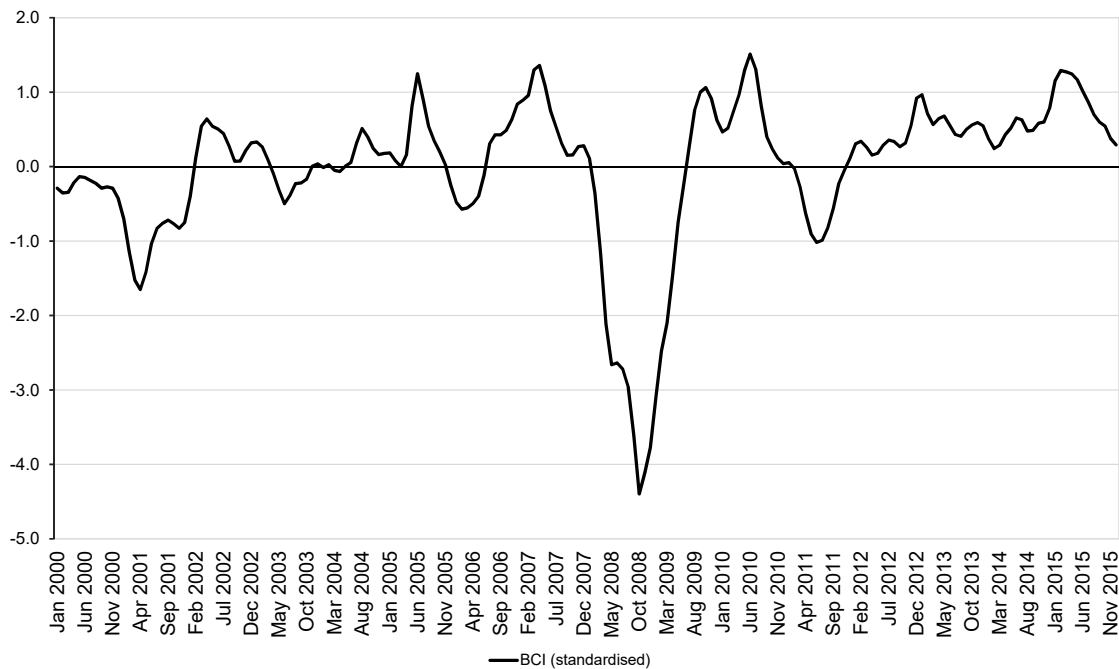


Figure 2: Business conditions index in Malta (2000 - 2015)

The BCI targets real business conditions at high frequency (see *Figure 2*). Its underlying indicators are seasonally adjusted monthly registered unemployment, industrial production, airline seat capacity servicing Malta, mortgage credit, tax revenues, the ESI, quarterly real GDP and the term-structure of interest rates.<sup>7</sup> The index aggregates high and low frequency information, and stock and flow data.

The average value of the index is zero. A value of zero indicates average business conditions. Increasingly larger positive values imply increasingly better-than-average conditions. On the other hand, increasingly negative values indicate increasingly worse-than-average conditions.

Assume, for example, that statistics indicate that the airline seat-capacity rose by 6.0% between August and September in a particular year, leading to an implied cumulative third quarter surge of, for example, 10.0% in annual terms. Once the model is updated, it will obviously lead to a new implied economic assessment. The new data would probably lead the model to a slightly more optimistic assessment of where the Maltese economy stood in mid-August. However, the upward revisions to the more recent inferences would be significantly less noticeable.

A fundamental aspect of models similar to this measure is the assumption behind the underlying dynamics that shape the position where the economy can be expected to be before a new observation is received. Those dynamics cause a significant degree of reversion towards some mean. This implies that a positive or a negative 6.0% annual growth rate for real GDP is not going to persist for a long time. This is not really an assumption behind the model, but rather a simple implication of the data. Any process which will fit observed data will have a degree of mean reversion.

<sup>7</sup>The ESI is not seasonally adjusted.

This property simply derives from the fact that, for example, the very strong negative GDP growth rates during the last recession were not something that was sustained for a historically extended period of time. This would be the case for specific sample periods to which this class of models are fit. Thus, for example, if the index is high above the mean of zero, the unconditional forecasts will always indicate that it is going to be headed back down. This might mislead interpretation into thinking about a worsening in business conditions. In that case, a more meaningful signal of a real worsening would be found if the index were to suddenly fall into negative territory.

While one must always interpret the index with caution, it is a helpful and convenient quantitative summary of how economic news would alter an objective and independent assessment of where the local economy currently stands. Moreover, one has to remember that this index attempts to measure business conditions, which are an unobserved variable.<sup>8</sup>

#### 4.1. Turning-point analysis

The Bry-Boschan routine finds turning points, both for peaks and troughs, in a given series.<sup>9</sup> Upon identifying the turning points, the sample period can be divided into phases of expansions or contractions between respective trough points and peak points.

Statistical information would then be available regarding various elements of these partitioned phases, including their duration and amplitude. Some restrictions are often imposed on the nature of economic phases. Thus, for example, a two-quarter minimum duration is often applied for expansions and contractions, which is in line with established definitions used in economics.<sup>10</sup>

The technique identifies three periods of contraction in the Maltese economy (see *Figure 3*). These occur in 2001, 2004, and between the last quarter of 2008 and the first quarter of 2009. In 2001, adverse external shocks hit the electronics industry and tourism – two important economic activities for Malta. The first was a slowdown of the global semi-conductors industry in the aftermath of the bursting of the US technology bubble in 2000.

Moreover, geopolitical tensions in the Middle East and their impact on world travel, depressed the local tourist industry. In 2004, Malta's accession into the European Union led to substantial restructuring in a number of specific sectors - particularly the local shipyards and the textile industry. The global crisis episode in late 2008 and early 2009, however, resulted in a severe shock to the local economy - with many sectors of the economy being affected simultaneously.

The BCI captures effectively the turning points in all the three contractions identified by the Bry-Boschan technique (see *Figure 4*). The 2001 crisis and the 2008/9 crisis are identified clearly, with the BCI indicating progressively worsening conditions multiple quarters ahead.

For example, the BCI begins to turn negative in early 2008, indicating worsening business conditions. This is confirmed by glancing at GDP figures published in that period. The first

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<sup>8</sup>In this respect, *Appendix 1* presents some simple stability tests.

<sup>9</sup>The routine does so defining a peak happening at time  $t$  if  $y_{t-k}, \dots, y_{t-k+1} < y_t > y_{t+1}, \dots, y_{t+k}$ , with a trough designated when  $y_{t-k}, \dots, y_{t-k+1} > y_t < y_{t+1}, \dots, y_{t+k}$ . The parameter  $k$  is set according to the frequency metric being used. Thus,  $k = 2$  for quarterly data,  $k = 5$  for monthly data and  $k = 1$  for yearly data.  $k$  is called the *Symmetric-Window parameter*.

<sup>10</sup>It has to be noted, however, that the National Bureau of Economic Research (NBER) does not define a recession explicitly in terms of two consecutive quarters of decline in real GDP, but rather defines it as effecting various broad economic indicators; For NBER, "...a recession is a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales" - NBER Business Cycle Dating Committee, dated 20.09.2010.

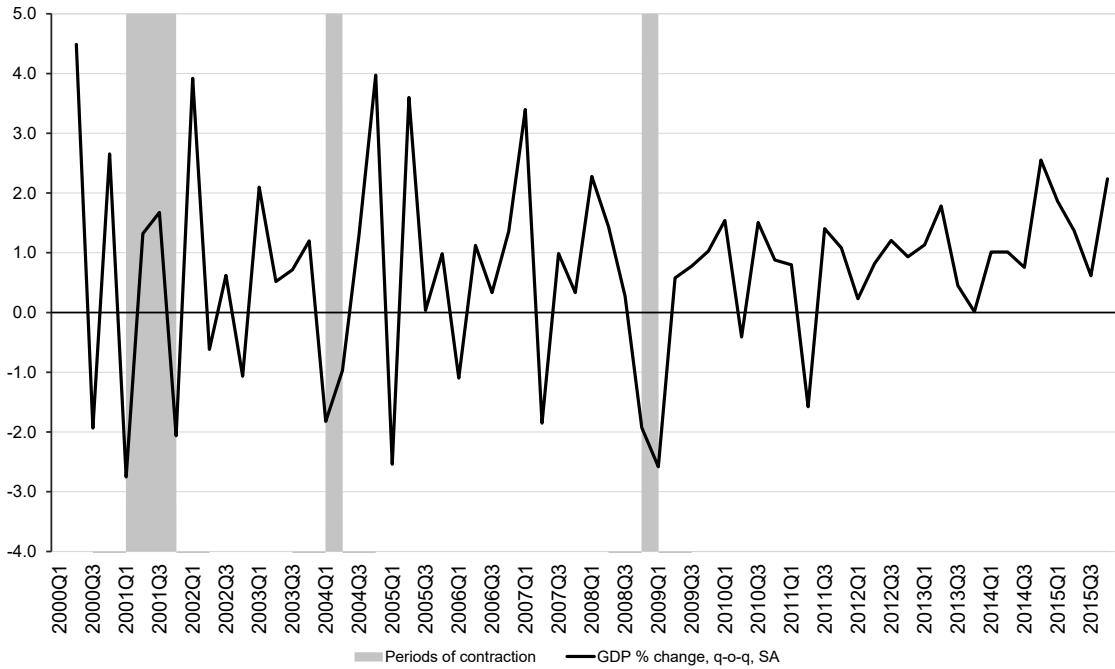


Figure 3: Periods of identified contractions and expansions in real GDP growth (SA)

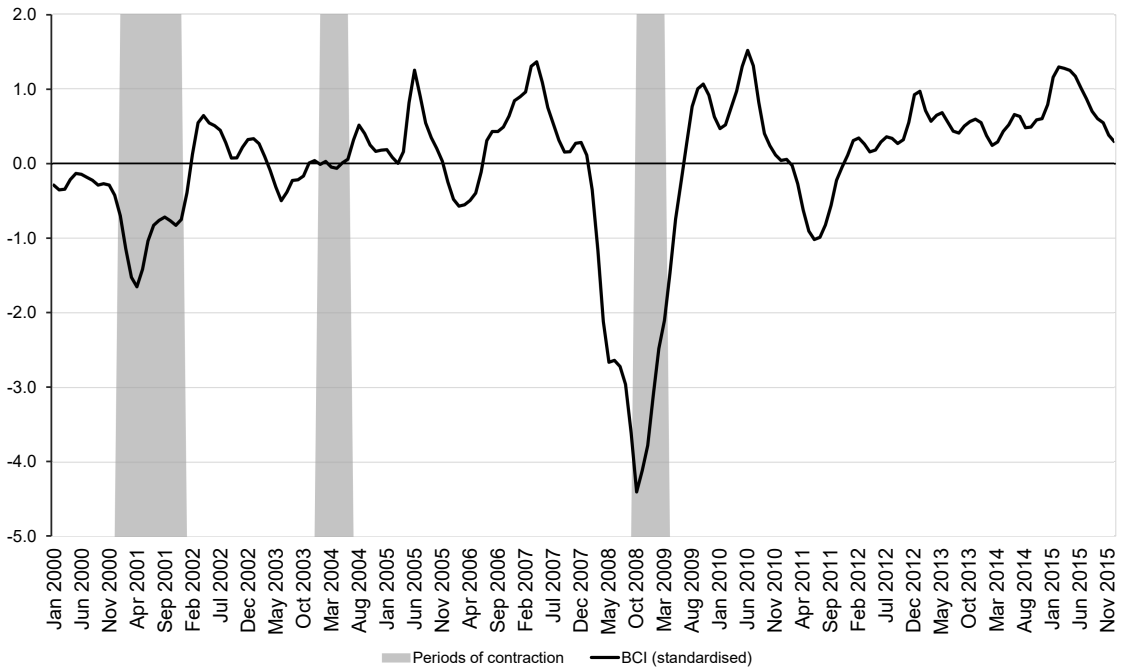


Figure 4: Identified turning points and the BCI

GDP vintage for the whole of 2008 indicated a very sudden and sharp slowdown in seasonally adjusted quarter-on-quarter growth rates from late 2007 to 2008.<sup>11</sup> Published quarter-on-quarter growth rates slowed down from 1.1% in 2007Q4 to 0.2% in 2008Q1, turning negative in 2008Q3, and worsening further in the final quarter of the year.

The 2004 episode also appears as a decrease in economic activity in the index, however in overall terms, these remain close to the average. Thus, it is not as severe as the other two episodes. One may speculate that the economic reforms and liberalisations enacted in the run-up to EU accession affected the dynamic of business conditions.

In addition, the BCI also identifies two further periods of lower-than-average business conditions. These occur in 2006 and in 2011. The former can be attributed to the tourist industry. In that year, inbound tourists fell significantly, with seat-capacity of airlines serving Malta falling markedly. By late 2006, however, tourist traffic was boosted by significant increases in flights served by low-cost carriers.

The lower-than-average business conditions episode in 2011 may reflect the intensification of the European sovereign debt crisis late that year. These centred on Malta's main trading partners, with uncertainty leading to a sharp deceleration in Maltese exports in the third quarter of 2011.

#### 4.2. BCI and the output gap

No quarterly estimates of the output gap are calculated by the Central Bank of Malta, and an annual measure does not depict fairly the dynamics behind the the two components. In that respect, an output gap was computed on the basis of HP filtered GDP volumes. Modelling the resulting output gap as a simple  $AR(1)$  process, augmented by a lag of the BCI yields a strongly significant relationship between the two variables, (see *Table 1*).<sup>12</sup>

The relative weakness of this equation may be down to the simplistic assumptions behind the imputed quarterly output gap. The findings appear to indicate the BCI's validity in capturing movements in the filtered output gap (see *Figure 5*).

Another quarterly output gap was derived by computing quarter-on-quarter growth rates in seasonally adjusted GDP volumes and in potential output. This was carried out to check the findings of the HP filtered output gap. A simple quarterly relationship was established as  $Output\ Gap = (GDP\ growth - Potential\ GDP\ growth)$ . This can be seen in *Figure 5*. This measure of the output gap is more volatile than the HP filtered calculation.

Overall, the BCI captures very accurately the pattern of both output gap variants. Also, the indicator appears to lead changes in the output gap.

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<sup>11</sup>National Statistics Office (NSO) News release No. 040/2009

<sup>12</sup>No moving average process was deemed to be required. The correlogram showed no partial autocorrelation or autocorrelation in the data following its treatment as a simple  $AR(1)$  process.

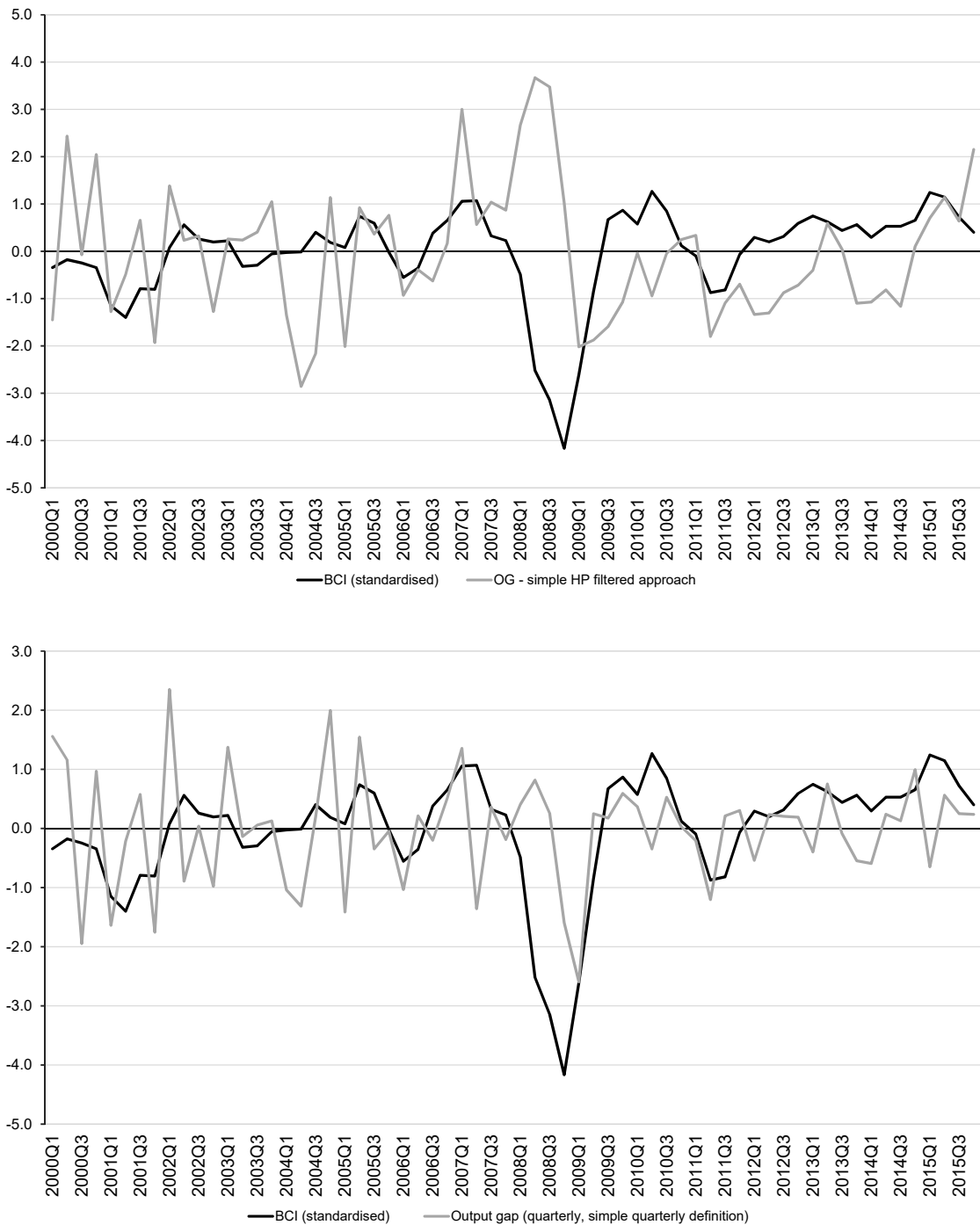


Figure 5: Standardised business conditions index (BCI), and a quarterly output gap derived from an HP filter (above) and a simple subtraction in quarterly rates (below)

Dependent Variable: OG MT  
 Method: ARMA Conditional Least Squares  
 Sample: 2000Q3 2015Q4  
 Included observations: 62 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BCI MT(-1)	0.2667	0.0739	3.6064	0.0006
AR(1)	-0.4369	0.1139	-3.8332	0.0003
R-squared	0.2560	Sum squared resid.		39.3729
Adjusted R-squared	0.2436	Log likelihood		-73.8984

Table 1: Simple AR(1) process, again augmented with a lagged BCI as an independent variable

#### 4.3. BCI and the European Commission's business climate indicator

A simple comparison can be made between this BCI and the business climate indicator for Malta published by the EC. As can be seen in *Figure 6*, the EC index's reliance on survey data provides a good indication of turning points around the average.<sup>13</sup>

It is apparent, however, that the BCI as calculated in this study results in a smoother and more stable measure of business conditions than the one published by the EC. This volatility, which may result from the use of survey data, do not follow *a priori* expectations on the slowly changing dynamics behind economic activity.

The amplitude of the two indices is similar, with the BCI providing a key, early indication of the likely direction of the EC's indicator (see *Figure 6*). If one models the overall business climate indicator as an *AR(1)* process, thus ensuring a clean correlogram, a lagged BCI returns a strong and statistically significant relationship (see *Table 2*).

<sup>13</sup>The business climate indicator is available from November 2002 onwards.



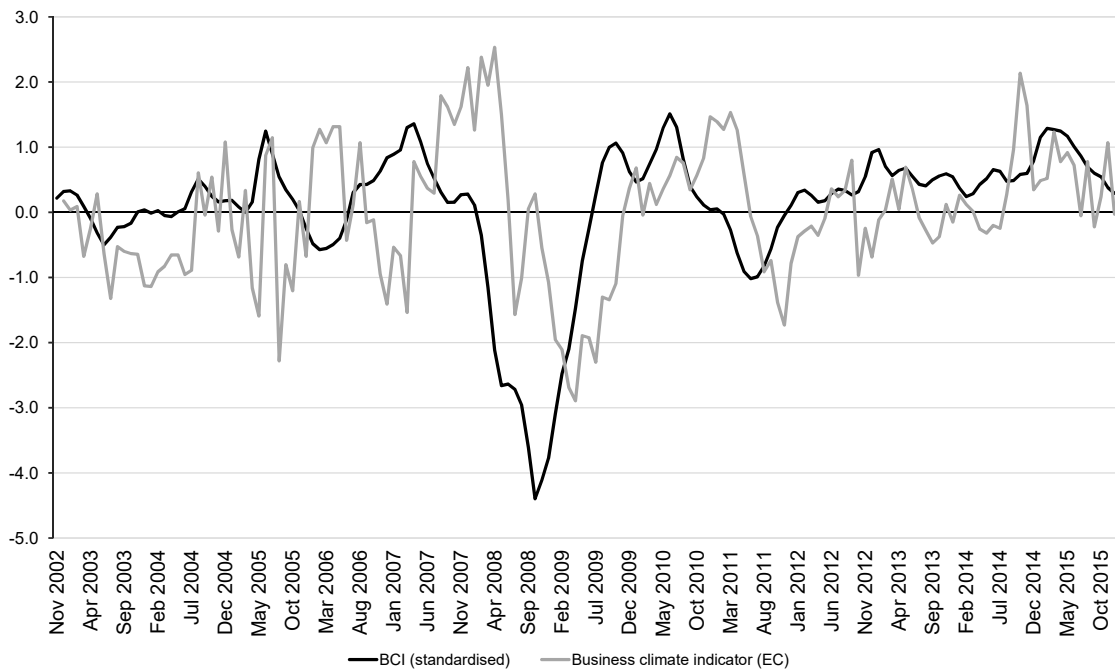


Figure 6: Business conditions index (BCI), and EC's business climate indicator in Malta (2007 - 2015)

Dependent Variable: EC Business climate indicator

Method: ARMA Conditional Least Squares

Sample (adjusted): 2002M12 2016M05

Included observations: 162 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BCI MT(-1)	0.3281	0.1358	2.4153	0.0168
AR(1)	0.6655	0.0605	10.9971	0.0000
R-squared	0.5239	Sum squared resid.		78.1559
Adjusted R-squared	0.5209	Log likelihood		-170.8280

Table 2: Simple AR(1) process, augmented with a lagged BCI as an independent variable

## 5. Conclusion

This paper illustrates a simple, understandable indicator on business conditions in Malta. The usefulness of this measure is linked with its availability at high-frequencies, and thus its ability to inform, in a timely manner, its eventual users - be they policymakers or the general public. Moreover, it appears to be a useful aid in bridging the gap between published GDP data and medium-term forecasts; its use in short-term forecasting and continued availability would serve to aid the forecasting of the local economy.

The indicator appears to capture accurately the historic turning points in the Maltese economy, and it compares well with other indicators such as a business climate indicator and an output gap estimate. Finally, as discussed in the Appendix, results are robust to changes in vintages, to the removal of GDP from the set of variables, and are more correlated with real growth in GDP than a principal-component type common factor.

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## 7. Appendix 1: Stability

The first stability test was based on the removal of quarterly GDP changes from the system. This was carried out on the basis of the magnitude of the revisions carried out to published GDP estimates in Malta. The resulting BCI which excludes GDP is not too dissimilar from the original version.<sup>14</sup> This might result from the relatively lower frequency of the GDP variable. The BCI measure excluding GDP takes longer to improve following the lower-than-average activity levels identified in 2006 (see *Figure 7*), and turns earlier into the crisis episode in late 2008, identified above. However, the aim of this study remains the creation of a business conditions index - ideally using data at mixed frequencies, rather than a tracker of GDP growth. Thus, GDP growth was retained in the final specification as it is seen to contribute key information to the business conditions index.

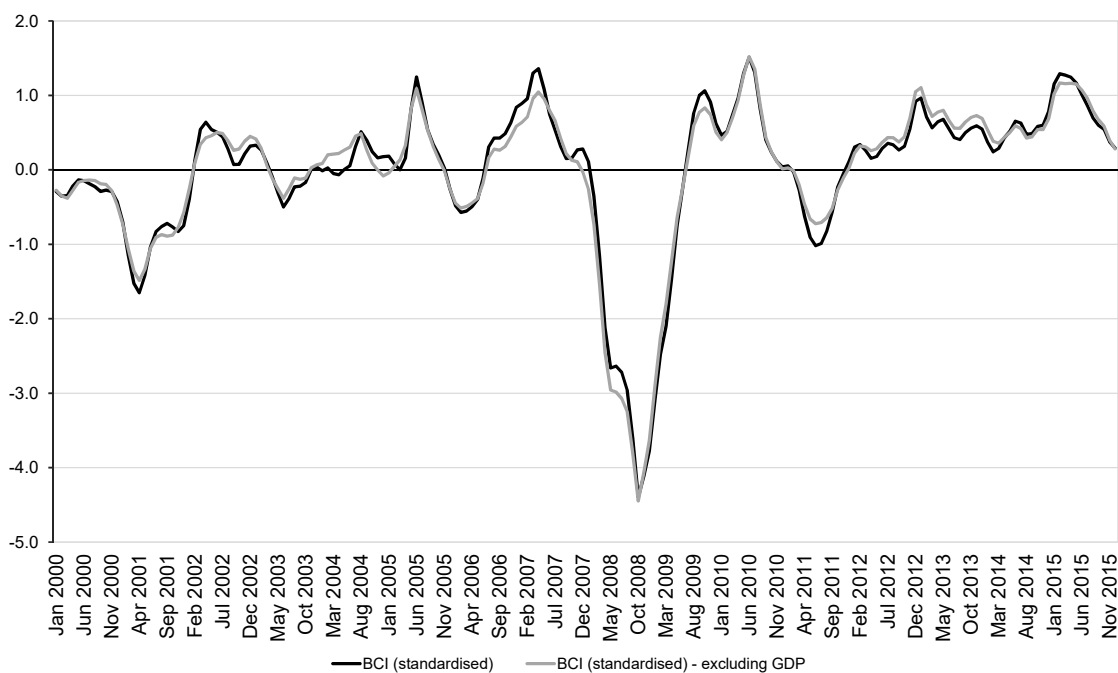


Figure 7: Standardised business conditions index (BCI), including and excluding GDP

The standardised business conditions indicator was also compared with a simple common factor obtained from principal-component analysis. To serve as a further robustness check, the principal-component analysis was carried out on a larger set of variables.<sup>15</sup> The ESI was removed from this further stage of stability testing to serve as a benchmark against which to test the performance of the BCI in capturing GDP. This variant of the indicator is termed 'lean' BCI.

The common-factor obtained from principal-component analysis was then computed as a simple three-month moving average, to smoothen out the volatility. The high noise element found in

<sup>14</sup>It has to be noted that the ADS (2009) approach does not identify the sign of the resulting index. Thus, in the specification that includes the GDP, the sign of the indicator is changed so it follows the same direction as GDP.

<sup>15</sup>These variables are overall industrial production, as well as eight subcomponents of industrial production, residential deposits, airline seat capacity and tourist arrivals.

	GDP growth	Common factor	Malta BCI	Malta ESI
GDP growth	1.00			
Common factor	0.31	1.00		
Malta 'lean' BCI	0.45	0.33	1.00	
Malta ESI	0.31	0.74	0.36	1.00

Table 3: Correlation matrix, (2006 - 2015)

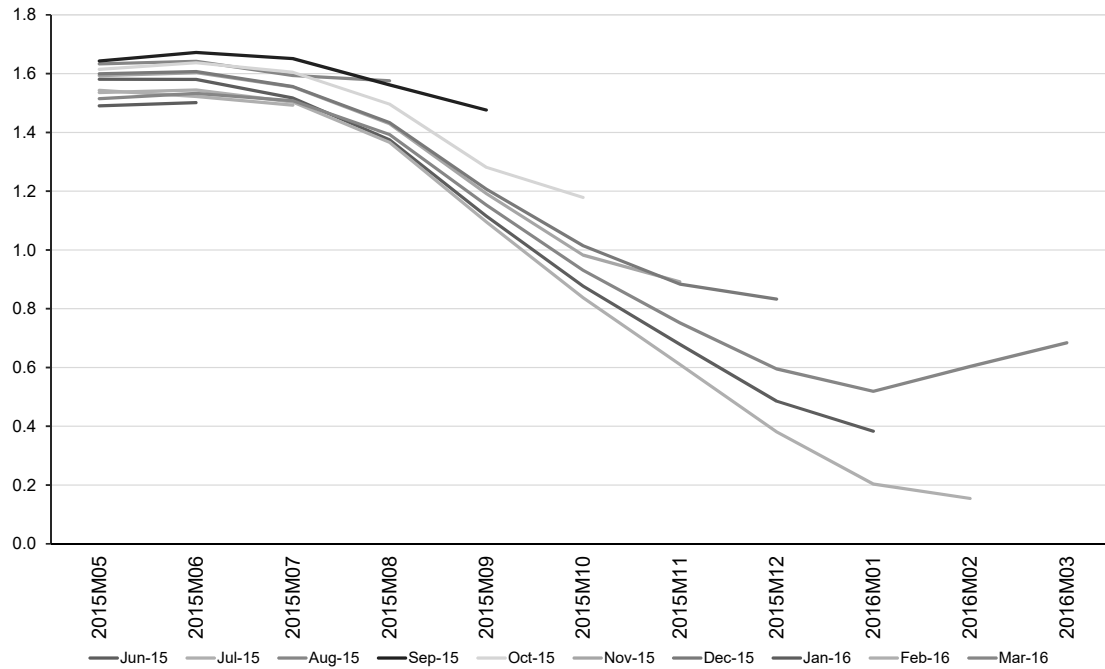


Figure 8: Successive vintages of the standardised business conditions index

local GDP growth figures, even when standardised and seasonally adjusted, lowers the overall correlation levels. The BCI, the statistical common factor, as well as the EC economic sentiment indicator in Malta are significantly smoother than published GDP growth rates.

Nonetheless, the 'lean' BCI - shorn of the ESI - outperforms both the common factor and the ESI in relating with standardised SA GDP growth (see *Table 3*).

Finally, a pseudo real-time analysis was carried out on the BCI, running the model with multiple data vintages for the ten months to March 2016. At any point  $\tau$  in real time, the respective  $\tau$ -data vintage is used to extract the economic activity factor.

As time progresses, the system is re-estimated, always using the latest vintage of data. In *Figure 8*, a 'tentacle plot' is shown for the ten months to March 2016.

These plots are several distinct series of the estimated business conditions resulting for the sequential vintage of 2015 and 2016 data. The plot shows ten paths, extracted with data available on the first day of each respective month.

With successive runs, the model updates its estimate of activity in the economy; although there are some differences in the indicator, the resulting estimates are quite stable, and the historical revisions moderate.