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A New Business Conditions Index for Malta*

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Abstract

This paper develops a new indicator of business conditions for the Maltese economy starting in January 2001. The index is based on a mixed-frequency dynamic factor model that efficiently handles a dataset of weekly, monthly, and quarterly information, covering several aspects of the economy. Similarly to the Business Conditions Index currently employed by the Central Bank of Malta, this new indicator tracks Malta's economic developments. In addition, it provides a decomposition of its fluctuations and shows that variables related to real activity and expectations of future economic activity are the main driving forces behind developments of business conditions. Finally, compared to the current Business Conditions Index, the new index appears to provide a similar narrative of Maltese economic fluctuations but appears to be less susceptible to changes in its historical values when updated with newly available data.

JEL Classification: C32, C55, E32.

Keywords: Business cycle, dynamic factor model, state-space model, large cross-section of data.

Contents

1 Introduction

Understanding developments in business conditions is of paramount importance in policy institutions. As economic conditions evolve, policy makers require a clear and timely assessment of the state of the economy to support their decision-making. However, such a process presents some challenges, as data are often released in a staggered manner and published with a lag, making any reliable evaluation of the health of the economy intrinsically difficult. This was particularly evident during the COVID-19 pandemic, when numerous and rapid developments left economic agents facing prolonged periods of increased uncertainty.

The academic literature presents numerous efforts of indices created with the specific aim of providing an assessment of economic conditions. In a seminal work by Stock and Watson (1989), the authors construct coincident and leading economic indicators using monthly data via a dynamic factor model (DFM) for the United States of America. Also for the US, Mariano and Murasawa (2003) develop a DFM that is able to draw relevant information from quarterly and monthly data to develop a coincident business cycle indicator. For the euro area, Altissimo et al. (2001) construct a monthly indicator of the business cycle by using a DFM model. The authors exploit the information contained in a rich harmonised monthly dataset for all member countries containing numerous variables with the aim to provide an almost exhaustive description of the European economy. These relate to industrial production, producer and consumer prices, interest rates, exchange rates and financial variables, various surveys, trade, and labour market data amongst others. In another contribution, Camacho and Pérez-Quirós (2008) set up a relatively smaller scale dynamic factor framework with quarterly, monthly, and survey-based data to produce a short-term indicator of eurozone growth, as well as its forecast. The authors also use a real-time dataset to show how data revisions and availability affect forecast results and uncertainty. Moreover, Aruoba et al. (2009) develop a mixed-frequency DFM to optimally extract the latent state of macroeconomic activity. Despite being estimated only on a limited number of series, it is also able to handle the information offered by data at a daily frequency.

The Central Bank of Malta has also contributed to this field of research by constructing an indicator that captures developments in the Maltese economy. As part of the European System of Central Banks (ESCB), the Bank plays a key role in pursuing the System's mandate of price stability, and therefore its ability of understanding changes in economic conditions in a timely manner is imperative for its decision-making. In this regard, Ellul (2016) develops a Business Conditions Index based on the work of Aruoba et al. (2009), similarly opting for a small number of variables in the estimation of the mixed-frequency DFM. This work was further refined in Ellul (2020), where the dataset was modified to better reflect the ever-evolving dynamics of the Maltese economy, and the index started to be estimated using year-on-year growth rates, as opposed to quarter-on-quarter ones. The Business Conditions Index (henceforth, Current BCI) is currently estimated on a monthly basis and is communicated to the public through a Central Bank of Malta's monthly economic update publication.

Despite being an unquestionably crucial tool in the Central Bank's suite of models, the Current BCI presents some limitations. First, being based on a limited number of variables, it might not necessarily encompass all the relevant aspects of the Maltese economy, thus not providing a comprehensive assessment of the country's business conditions. Second, as a consequence of the small dataset, it might be prone to substantial changes in its past values when updated with newly available information. This is especially the case when large revisions to previous values of gross domestic product (GDP) occur, causing economic agents to revise their understanding of past economic performance. Third, the model does not provide a decomposition of the index into contributions of the underlying variables in the dataset, thus providing only a limited comprehension of the underlying forces driving its fluctuations. Fourth, the Current BCI is estimated only using quarterly and monthly data because, from a communications point of view, a monthly update on such an index is deemed to provide an adequate picture of the economy to the public. Despite this, recent advances in the academic literature have demonstrated how higher-frequency data would add relevant information that should not be omitted.

In this paper, we aim to overcome the limitations of the existing Maltese BCI adopted by the Central Bank of Malta, by leveraging recent advances in econometric literature. Specifically, we develop a New Business Conditions Index (henceforth, New BCI) by closely following the approach outlined in Baumeister et al. (2024) and further employed in Bańbura et al. (2024). More precisely, we build a dataset of quarterly, monthly, and weekly series for the Maltese economy, and estimate a mixed-frequency DFM to generate the new indicator. Although Malta is part of the euro area and, as such, is included in Bańbura et al. (2024), our indicator differs from that produced in the latter study. Specifically, the index in Bańbura et al. (2024) is generated on the basis of a harmonised dataset for all countries in the monetary union. By contrast, we compile our own large dataset with the aim of better reflecting the specific features of the Maltese economy. Moreover, this approach helps mitigate potential data availability issues that may arise when relying on homogeneous data across heterogeneous economies.

We find that the New BCI broadly confirms the narrative of the current index, as it is able to track reasonably well the developments in the Maltese economy. We also present a decomposition of the index into its driving forces to show its sources of fluctuation. The results show that various variables play a relevant role in the developments of business conditions, most of them pertaining to real economic activity or expectations about future economic activity. Subsequently, when we scale the index to compare it with real GDP growth for Malta, we illustrate how it can track changes in this key measure of economic activity, and how it can serve as a tool to inform both policymakers and the public about current economic conditions. Finally, we provide a formal evaluation of the stability of the New BCI vis-à-vis the current one, and demonstrate how the former is less subject to changes in its past values when new data become available or when faced with data revisions.

The rest of the paper is organised as follows. Section 2 outlines the main literature we refer to. Section 3 provides an overview of the methodology adopted and subsequently continues with a detailed description of the variables used to build the mixed-frequency dataset. Section 4 presents the main results. Specifically, it shows the index and the contributors of its fluctuations, how it compares with the Current BCI, and a comparison of the two indices with the growth in real GDP. Moreover, it provides an assessment of the stability properties of the two indices across data vintages. Finally, Section 5 concludes.

2 Related literature

This paper builds on the economic literature that adopts comprehensive datasets to extract relevant information for assessing the state of the economy. This literature was pioneered by Stock and Watson (1989) and was followed by notable works such as Mariano and Murasawa (2003) and Aruoba et al. (2009).

In addition, this work contributes to the recent literature that has drawn attention to the value of high-frequency data in tracking economic conditions in real time. The growing interest was spurred by the sharp and abrupt changes in economic conditions worldwide triggered by the outbreak of the COVID-19 pandemic. As a result, this literature has witnessed a proliferation of indicators capable of handling high-frequency observations, as well as information obtained from previously unexplored sources, with the aim of producing more timely and accurate indicators of economic conditions. Following its launch in the first quarter of 2020, the indicator developed by Lewis et al. (2020) for the US generated further interest in this area of research, not only domestically but also in several other countries. Consequently, Lewis et al. (2022) develop a weekly economic index to track developments in the US and show how this index behaves during the first ten months of the pandemic. The authors adopt a DFM and make use of ten weekly variables, eight of which are available in almost real time, i.e., the Thursday after the reference week.

For Germany, Eraslan and Götz (2020) construct a weekly activity index by taking timely and rather unconventional high-frequency variables and two lower frequency macroeconomic indicators. The former include an index on daily truck troll mileage, electricity consumption, and pedestrian frequency in selected shipping districts in some of the country's large cities, while the latter refer to industrial production and GDP. Turning to Portugal, Lourenço and Rua (2021) utilise five non-traditional variables in their study. These include data on traffic, data on electricity consumption, data on the movement of passengers at national airports, the number of aircraft landed, and freight movements. The data are then cast into a factor model to obtain a daily economic indicator. Wegmüller et al. (2023) develop a weekly economic activity indicator for Switzerland based on nine high-frequency variables using a linear DFM. In this study a measure of air pollution is used together with a measure for rail freight transport and electricity consumption, amongst other indicators.

In contrast to several studies in the recent literature, Baumeister et al. (2024) and Bańbura et al. (2024) employ a relatively richer dataset, that goes beyond a handful of series. Baumeister et al. (2024) compile datasets of variables at different frequencies for each US state, large enough to encompass the several aspects and peculiarities of the US economy. Subsequently, the state-level datasets feed a mixed-frequency DFM, designed to handle quarterly, monthly, and weekly observations, as well as any path of missing data, to construct economic condition indices for each state. In addition, the authors decompose the state-level indices to show the contributors of the state-specific economic fluctuations. In the same spirit, Bańbura et al. (2024) develop a Harmonised Weekly Activity Index (HaWAI) for the countries belonging to the euro area by closely following the mixed-frequency DFM developed in Baumeister et al. (2024).

In a different approach, Woloszko (2020) develops a weekly tracker utilising Google Trends search volume indices to measure economic activity for 46 OECD and G20 countries. More recently, Ghezzi et al. (2026) propose a new economic modelling approach to measure economic activity exploiting highly granular spatio-temporal data used to extract a common factor able to summarise hourly economic activity at the ZIP code level in the County of San Diego, California. Despite the richness and granularity of the information they provide, many of these microeconomic datasets are characterised by short time series, limiting their suitability for the construction of long-term economic activity indicators.

Finally, part of the recent literature has continued to rely on DFMs to summarise the information contained in conventional monthly and quarterly macroeconomic datasets. These studies have shown how DFMs remain effective for real-time monitoring of economic activity, even during the unprecedented disruptions caused by the COVID-19 pandemic. Examples are Hartigan and Rosewall (2024) and Bayarmagnai (2025) for Australia and New Zealand, respectively.

3 Methodology

This section outlines the methodology implemented in this paper and the dataset adopted in the estimation. First, the mixed-frequency DFM is outlined, and then we provide a description of the data used to build our dataset by group classification.

3.1 The model

For the development of the New BCI we resort to the framework developed in Baumeister et al. (2024) and subsequently employed in Bańbura et al. (2024). As a DFM, the model summarises the information contained in a set of N indicators conveying information on economic conditions, into a single common latent factor driving the dynamics of the whole system. The framework combines data sampled at different frequencies, to generate high-frequency indicators, specifically by mixing quarterly, monthly, and weekly observations. Moreover, it is able to deal with any path of missing data, which is a desirable feature when operating with data that are released in a non-synchronous way or having different sample sizes.

The base frequency of the observations is weekly. Furthermore, lower frequency data, i.e., monthly or quarterly, are also treated as weekly series but with missing observations.[1] Let $y_{i,t}$ denote the i^{th} observed indicator, properly transformed and standardised, and $t = 1, ..., T$ denote the number of weeks in the sample. Such indicator is assumed to be composed of a common and an idiosyncratic component. The former is a common factor f_t times the indicator-specific factor loading λ_i, while the latter captures the indicator-specific features that go beyond the dynamics summarised by the factor f_t. More formally:

$$y_{i,t} = \lambda_i f_t + u_{i,t} \tag{1}$$

for $i = 1, ..., N$. Moreover, both the common factor f_t and the idiosyncratic components $u_{i,t}$ follow autoregressive processes:

$$f_t = \varphi_1 f_{t-1} + \cdots + \varphi_p f_{t-p} + \epsilon_t, \tag{2}$$

$$u_{i,t} = \psi_{i,1} u_{i,t-1} + \cdots + \psi_{i,q} u_{i,t-q} + e_{i,t}, \tag{3}$$

where $\epsilon_t \sim N(0, \sigma^2_\epsilon)$ and $e_{i,t} \sim N(0, \sigma^2_{e_i})$, while p and q denote the lag orders.[2]

The model is cast into a state-space representation and estimated using a Bayesian approach. The Gibbs sampling routine alternates between draws from the posterior distributions of the parameters and of the latent common factor. The simulation smoother developed in Carter and Kohn (1994) accounts for any pattern of missing data. As such, it enables the reconstruction of series with missing observations and the interpolation of lower-frequency data into weekly ones.[3]

Once the model is estimated, the New BCI is derived as follows:

$$New\, BCI_t = (\Lambda'\Lambda)^{-1}\Lambda'\widehat{Y_t} \tag{4}$$

for $t = 1, ..., T$. In Equation (4) $\Lambda = [\lambda_1, ..., \lambda_i, ..., \lambda_N]'$ represents a vector collecting the median draws of the factor loadings, while $\widehat{Y_t} = [\widehat{y_{1,t}}, ..., \widehat{y_{i,t}}, ..., \widehat{y_{N,t}}]$ denotes the smoothed series, i.e., the economic indicators transformed into complete weekly series through the model's ability of interpolating missing observations.[4]

[1] Monthly and quarterly observations in the dataset are recorded in the last week of their respective reference month or quarter. As the end of the week does not always coincide exactly with the end of the month or quarter, minor timing discrepancies may occur. However, these do not materially alter the analysis.

[2] To allow for persistence in the dynamics of both the common factor and idiosyncratic terms, we follow Baumeister et al. (2024) and set the lag orders to $p = 4$ and $q = 4$.

[3] In this section, we only provide a broad overview of the DFM framework by outlining its main features. For a detailed description of the model, choice of the priors and associated estimation algorithm, please refer to Baumeister et al. (2024).

[4] While the New BCI is based on posterior median draws, it is also possible to consider its credible region in order to evaluate the uncertainty associated with its estimate.

3.2 The data

We estimate the DFM outlined in the previous subsection on a broad range of weekly, monthly, and quarterly variables covering various aspects of the Maltese economy. The choice of such variables is dictated by the necessity of providing comprehensive information about the main drivers of the country's economic activity. The variables are classified into four categories, each reflecting a specific segment of interest from a policy perspective: real activity, expectations, financial conditions, and international trade. This classification proves useful when assessing the contribution of each group to the fluctuations in overall business conditions. We first describe the series included in the dataset, together with the rationale for their selection, and then provide summary information on the frequency, transformation, and range of the data in Table 1. The raw data are collected as of the 13 March 2026 and cover observations from the first week of January 2000 until the last week of February 2026.[5] Many series are then transformed in year-on-year terms, thus making the New BCI start from the first week of January 2001.[6]

Real activity

We include real GDP as a key measure of economic activity. We then include the quarterly services turnover indicator in real terms to provide information on business turnover in the services sectors, which is highly relevant for a services-based economy like Malta. Values in real terms are obtained by using services HICP as a deflator. Monthly variables such as the index of industrial production excluding energy and a measure of real tax revenue are added, with the latter obtained by summing up monthly tax receipts and then deflating by HICP.[7] In addition, we include an index of volume of sales in retail trade.

Labour market data, which comprise the monthly unemployment rate and quarterly variables such as total employment and real compensation of employees deflated by the GDP deflator, are also included in this category. By doing so, we provide information on both the remuneration and the number of individuals employed in the labour market.

The tourism sector is one of the key contributors to the Maltese economy. In 2025, the

[5] We collect data as of this date for two reasons. First, it allows the inclusion of the latest available GDP data for 2025, released at the end of February 2026. Second, it is consistent with the Central Bank of Malta's publication practices, whereby the monthly economic update is based on data available as of the middle of the month following the reference period.

[6] Please refer to Appendix A.1 for further details on the data sources and transformations. Please also refer to Appendix A.2 for stationarity checks. All standardisations are performed using the z-score transformation, whereby each observation is centred at zero by subtracting the sample mean and scaled by dividing by the sample standard deviation.

[7] We use the index of industrial production which excludes the production of energy for a specific reason. As of 2025, up to 30% of the electricity mix in Malta was made of electricity imported through the Malta-Sicily interconnector, which links the Maltese power grid with the Italian one. The interconnector was built in 2015 with the aim of satisfying the country's energy needs in excess of the supply capabilities provided by the Maltese gas-powered electricity generation facility located in Delimara. Such a percentage is believed to increase further in the future, especially in light of the project for the construction of a second interconnector to Sicily, which is expected to be operational in 2027. As such, a measure of overall industrial production would give a distorted measure of economic activity in the country.

Maltese islands welcomed approximately four million visitors, marking a 13% increase in total arrivals compared to the previous year. To capture developments in such an important industry, we include the monthly number of inbound tourists, excluding cruise ship passengers, and the monthly tourism expenditure deflated by headline HICP.

Expectations

Expectations regarding future economic conditions have implications on shaping business conditions as they can influence the current behaviour of economic agents. A key indicator in this category is the European Commission's Economic Sentiment Indicator (ESI), which is a broad survey-based measure capturing the perceptions of consumers as well as representatives from the manufacturing, services, retail trade, and construction sectors. In addition, we add building permits to provide information about prospective activity in the construction sector, which is a major contributor to the country's economic output, particularly during the recent decades of population growth.

Additional information on the perception about future economic conditions can be drawn from the term structure of local sovereign interest rates, which measures the relationship between interest rates over different maturities. We calculate a measure of the term spread by taking the difference between the offer rate for the ten-year sovereign bond yield for Malta (ISMA definition) and the offer rate on the secondary-market for the three-month Treasury bill, as done in Ellul (2016). This quasi-daily data is averaged out into weekly observations. A widening of the term spread could signal expectations of increased economic turbulence in the future.[8]

Another relevant factor is uncertainty, and to take this into account, we include the Central Bank's Economic Policy Uncertainty (EPU) Index.[9] The index, developed in Sant and Spiteri (2024), tracks fluctuations in the level of uncertainty of economic agents in relation to economic policy in the Maltese economy on a monthly basis. Indeed, uncertainty about economic policy has been demonstrated to lead to contractions in economic activity and increased volatility in financial markets (Caldara and Iacoviello, 2022).

Financial conditions

Financial markets are widely recognised as conveying insights into current and future economic conditions. To capture the sources and magnitude of funding available to economic agents, we include the Central Bank of Malta's measures of the credit gap for households and firms, as developed in Gatt (2024). These indicators assess the level of outstanding credit in the economy relative to their macroeconomy-implied trends. Additionally, we include data relative to the issuance of real debt securities and quoted

[8]This interpretation relies on the yield curve being upward sloping. In contrast, when the yield curve is inverted, a widening term spread may convey a different economic signal, such as heightened recession risk.

[9]Recent literature has shown a link between uncertainty and economic conditions. Seminal studies in the field, e.g., Bloom (2014), note how heightened economic uncertainty tend to dampen economic activity.

shares for both monetary and financial corporations (MFCs) and non-financial corporations (NFCs). These variables are at a quarterly frequency.

We also include measures that reflect the conditions of the financial markets, such as the monthly 10-year Maltese bond yield as an indicator of market expectations regarding future economic conditions. We incorporate the monthly country spread, calculated as the difference between the 10-year Maltese government bond yield and the 10-year German Bund yield. This serves to gauge the country's overall perceived level of risk. Next, we include the weekly shadow rate relative to the euro area developed in Krippner (2020) as a broad indicator of the monetary policy stance of the European Central Bank (ECB), during periods of conventional and unconventional policies. In addition, the Malta Stock Exchange (MSE) index is added to this category, at a weekly frequency, to further measure the performance of the Maltese market.[10]

International trade

Malta is a small economy characterised by a very high integration in international markets. To factor in this peculiarity, it is crucial to include indicators related to its trading activity. We therefore account for real exports and imports of goods.[11] Furthermore, we add the real effective exchange rate (REER) to gauge the Maltese competitiveness on international markets, as this influences the country's trade flows.[12] Finally, we include the Baltic Dry Index (BDI), which is a global indicator that tracks the cost of shipping dry bulk commodities by sea. Although it is not directly linked to Malta, the BDI serves as a useful proxy for global goods transportation and, by extension, for the Maltese trade sector, given the country's high degree of openness and integration in international markets. The relevance of this measure was particularly pronounced during the rebound in economic activity following the COVID-19 pandemic, when shipping costs surged due to the reopening of global trade.[13]

[10]This index, which tracks Maltese listed stocks, is largely driven by developments in the domestic banking sector. It is calculated in real-time throughout the trading day and weighted according to the current market capitalisation of its constituents. The MSE Index is based on the latest closing trade prices of the shares of all eligible companies. Further information is available as follows: MSE Index Methodology.

[11]The New BCI also accounts for exports of tourism services, an important component of overall services exports, in a separate indicator as explained previously.

[12]The REER is calculated as the inflation-adjusted value of the euro against the currencies adopted by the economies Malta primarily engages with in international trade.

[13]A substantial literature justifies the BDI as a leading indicator of global economic activity and trade. For a non-exhaustive overview please refer to Bakshi et al. (2010), Papailias et al. (2017) and Said and Giouvris (2019), among others.

Table 1: Variables included in the dataset for Malta, their classification into categories, transformation, frequency and range.

Category	Variable	Transformation	Frequency	Range
Real Activity	Real GDP	Y-o-Y Growth	Q	2000Q1 - 2025Q4
	Real Compensation of Employees	Y-o-Y Growth	Q	2000Q1 - 2025Q4
	Employment	Y-o-Y Growth	Q	2000Q1 - 2025Q4
	Real Services Turnover	Y-o-Y Growth	Q	2000Q1 - 2025Q4
	Unemployment Rate	Annual difference	M	2000M01 - 2026M01
	Inbound Tourism	Y-o-Y Growth	M	2000M01 - 2026M01
	Real Tourism Expenditure	Annual difference	M	2001M01 - 2026M01
	Industrial Production	Y-o-Y Growth	M	2000M01 - 2026M01
	Real Tax Revenue	Y-o-Y Growth	M	2000M01 - 2026M01
	Retail Trade	Y-o-Y Growth	M	2000M01 - 2026M01
Expectations	ESI	Level	M	2002M11 - 2026M02
	EPU	Level	M	2004M01 - 2026M02
	Building Permits	Annual difference	M	2005M01 - 2026M01
	Term Spread	Annual difference	W	2000W05 - 2026W08
Financial Conditions	Household Credit Gap	Level	Q	2000Q1 - 2025Q4
	Firm Credit Gap	Level	Q	2000Q1 - 2025Q4
	Real Debt Securities MFCs	Y-o-Y Growth	Q	2004Q1 - 2025Q4
	Real Debt Securities NFCs	Y-o-Y Growth	Q	2004Q1 - 2025Q4
	Real Quoted Shares MFCs	Y-o-Y Growth	Q	2004Q1 - 2025Q4
	Real Quoted Shares NFCs	Y-o-Y Growth	Q	2004Q1 - 2025Q4
	Malta 10-year Gov Bond Yield	Annual difference	M	2000M01 - 2026M02
	Country Spread	Annual difference	M	2000M01 - 2026M02
	MSE Index	Y-o-Y Growth	W	2000W01 - 2026W08
	EA Shadow Rate	Annual difference	W	2000W01 - 2026W08
International Trade	BDI	Annual difference	M	2000M01 - 2026M02
	REER	Annual difference	M	2000M01 - 2026M01
	Real Exports	Y-o-Y Growth	M	2002M01 - 2025M11
	Real Imports	Y-o-Y Growth	M	2002M01 - 2025M11

Notes: Term spread data are available at a weekly frequency from the first week of January 2002 onwards. Data relative to 2000 and 2001 are available at a monthly frequency. For these years, term spread is treated as a weekly series with missing observations. The ESI enters in levels in a similar spirit to Giannone et al. (2008).

4 The New Business Conditions Index

This section introduces the results obtained by estimating the model in Section 3.[14] We begin by presenting the New BCI and provide a breakdown of its fluctuations, showing how the contributions of the different categories have evolved over time. We compare the new index with the estimate of the BCI currently adopted by the Bank to show similarities and highlight differences in the two. Additionally, we compare both BCIs with real GDP growth to appreciate how developments in the indices are reflected in economic growth as indicated by the latter. Finally, we study how stable the New BCI is across vintages of data and compare its stability properties with those characterising the Current BCI. We do so by compiling a series of subsequent vintages, aiming at recreating the information available in specific points in time as would be used for the Bank's economic update, and then assess the magnitude of changes in the observations of the two indices.

4.1 The index and its drivers

Figure 1 shows the New BCI at a weekly frequency. Specifically, we show the median draw and the 68% credible region. The index is standardised and centred around zero, such that zero corresponds to average economic conditions. Positive (negative) values indicate conditions above (below) average. The index is expressed in year-on-year terms, with each observation capturing changes in the prevailing conditions of the economy relative to the corresponding week of the previous year.

The New BCI appears to be capable of capturing the ever-evolving economic conditions of the Maltese economy in a timely manner and is also seen to be able to track the magnitude of such developments through time. For example, the index shows that during 2001 and 2004 economic conditions were worse than average. This period was characterised by subdued activity, with the slowdown of the global semiconductor industry in the aftermath of the burst of the dot-com bubble (Ellul, 2016). This impacted the electronics industry, especially one of Malta's main exported goods at the time, namely semiconductors. In addition, following the 9/11 terror attacks, the tourism sector was adversely influenced. For 2004, changes in business conditions can be linked with the impact of the country's entry into the European Union on several sectors in the manufacturing industry, which led to substantial restructuring particularly in the local shipyards and textile industries (Ellul, 2016, 2021).

Furthermore, the impact that the 2008-2009 Great Recession had on the Maltese economy is clearly reflected in the index, as the latter presents a large and prolonged dip indicating business conditions well below average. The index fell from 0.6 in the first week of 2008 to -2.5 during the last week of May 2009, coinciding with an increase in the unemployment rate and a lower level of tourism activity. The Maltese economy also faced lower investments, with weaker external demand, cautious consumer spending, and

[14] All the results are based on posterior distributions approximated by 3,000 draws, retained after discarding 1,000 to minimise the influence of initial conditions. Convergence diagnostics are shown in Appendix B.1.

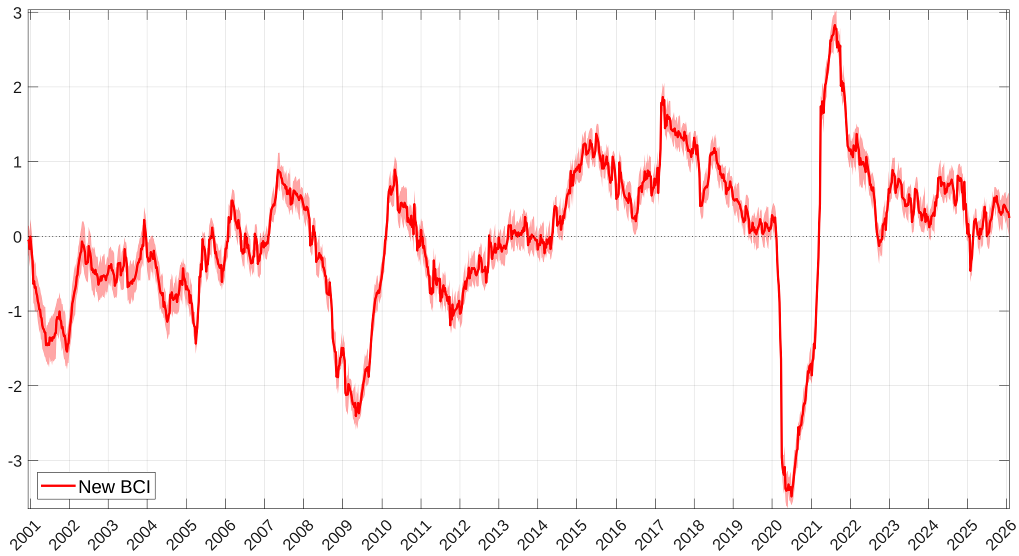
a lower level of turnover in the manufacturing industry (Central Bank of Malta, 2009). Following the crisis, an improvement in the real effective exchange rate and a recovery in foreign demand contributed to an improvement in Maltese exports (Grech, 2015). A recovery in business conditions is reflected in the index in early 2010, whereby the average of zero was met during the first week of March and continued to recover, rising to 0.9 by the end of May 2005. However, between 2011 and 2012, a relatively smaller dip was registered, with the index falling to -1.2 at the end of October 2011. This could possibly reflect developments in trade, particularly a slowdown in exports following the aforementioned recovery, in conjunction with concerns on the European sovereign debt crisis (Ellul, 2021).

The indicator clearly detects the period of robust economic activity that takes place from 2014 onwards and the abrupt decline that occurred in 2020 and early 2021 as a consequence of the outbreak of the COVID-19 pandemic. The New BCI fell from 0.3 during the last week of February 2020 to an all time low of -3.6 during the last week of July 2020. During this period, the contraction in economic activity was influenced by adverse developments in net exports, domestic demand, and worsening conditions in the services sector. In addition, the tourism industry was severely affected by the travel restrictions imposed worldwide and the resulting decline in demand among travellers.[15] The index then captures the recovery in economic conditions shortly after that, whereby it reached a high of 2.9 during the first week of September 2021.

During the following years, the index mostly presented above-average values, reflecting robust labour market conditions, favourable developments in the tourism sector, and strong real GDP growth.

[15] Both the Grand Harbour and the Maltese international airport were closed to passengers between mid-March 2020 and June 2020, in a bid to contain the spread of the pandemic. This resulted in the complete absence of inbound tourism during the period.

Figure 1: The New Business Conditions Index at a weekly frequency. Median draw (red solid line) and 68% credible region (red shaded area).



Source: Authors' calculations.

Notes: The x-axis represents time while the y-axis the value of the New BCI.

In addition to providing the overall index, the model outlined in Section 3 decomposes the New BCI into the contributions attributable to the underlying variables in the dataset, which we grouped into the four categories. From Equation (4), the contribution of category c to the New BCI can be formally obtained as follows:

$$Contribution_{c,t} = (\Lambda_c' \Lambda_c)^{-1} \Lambda_c' \widehat{Y_{c,t}} \tag{5}$$

for $c = 1, ..., 4$ and $t = 1, ..., T$, where Λ_c and $\widehat{Y_{c,t}}$, respectively, represent factor loadings and smoothed series belonging to category c.

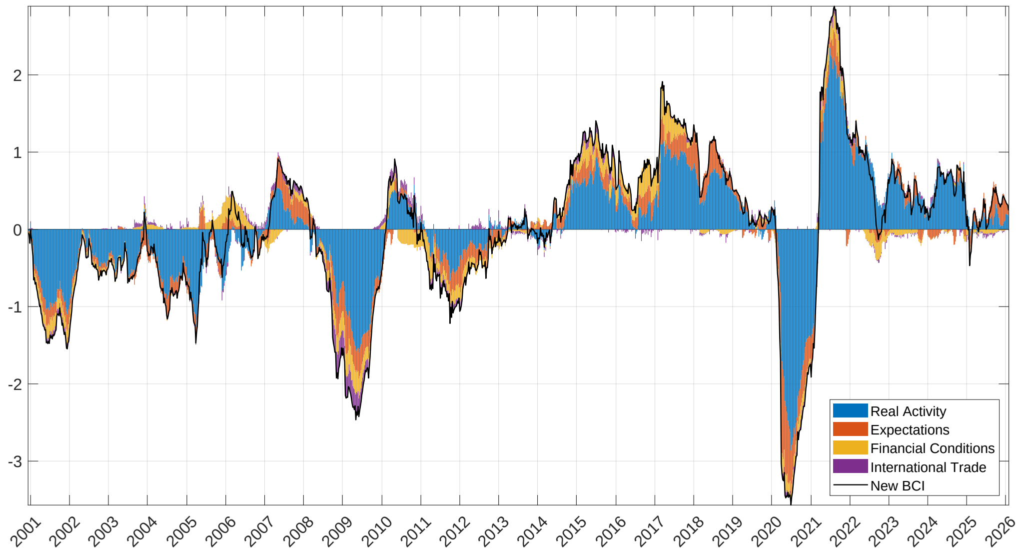
Figure 2 depicts the New BCI together with its decomposition.[16] As expected, real activity is the main contributor to Maltese business conditions fluctuations, with expectations also seen as a major driver over the years.[17] Interestingly, expectations tend to move in tandem with real activity in shaping the conditions indicator. The financial conditions category also appears to have a tendency to lead economic conditions, likely due to it encompassing variables that capture the facilitation of firm investment and the support to households' property purchases. Furthermore, it contributed negatively in

[16]The adoption of a single common factor implies that such a decomposition stems from a purely mathematical calculation and not from category-specific factors that were statistically isolated. In addition, Figure B.4 in Appendix B.2 shows the median draw and 68% credible region of each category, enabling an evaluation of their significance at each point in time.

[17]Together with financial conditions, the real activity category is the richest by number of variables. As such, it might not always be straightforward to deeply understand the contribution of variables belonging to, for example, either the labour market or the tourism industry. To facilitate interpretation, the model allows to identify variable-specific contributions. Specifically, Figure B.5 in Appendix B.3 shows the median values of the smoothed and standardised transformed series belonging to this category, as an additional output of the DFM approach employed for the estimation of the New BCI. Studying the fluctuations of these variables helps understand their contribution within the category. Figures B.6 to B.8 display similar information for the remaining three categories.

2022 until mid-2023, likely due to the tightening monetary policy measures implemented by the ECB to contain the surge in inflation. Finally, international trade helps explain Malta's subdued economic activity during the Great Recession of 2008 and 2009, likely reflecting the high sensitivity of its open economy to export and import demand.

Figure 2: The New Business Conditions Index at a weekly frequency. Median draw (black solid line) and contribution from the four categories (coloured shaded areas).



Source: Authors' calculations.

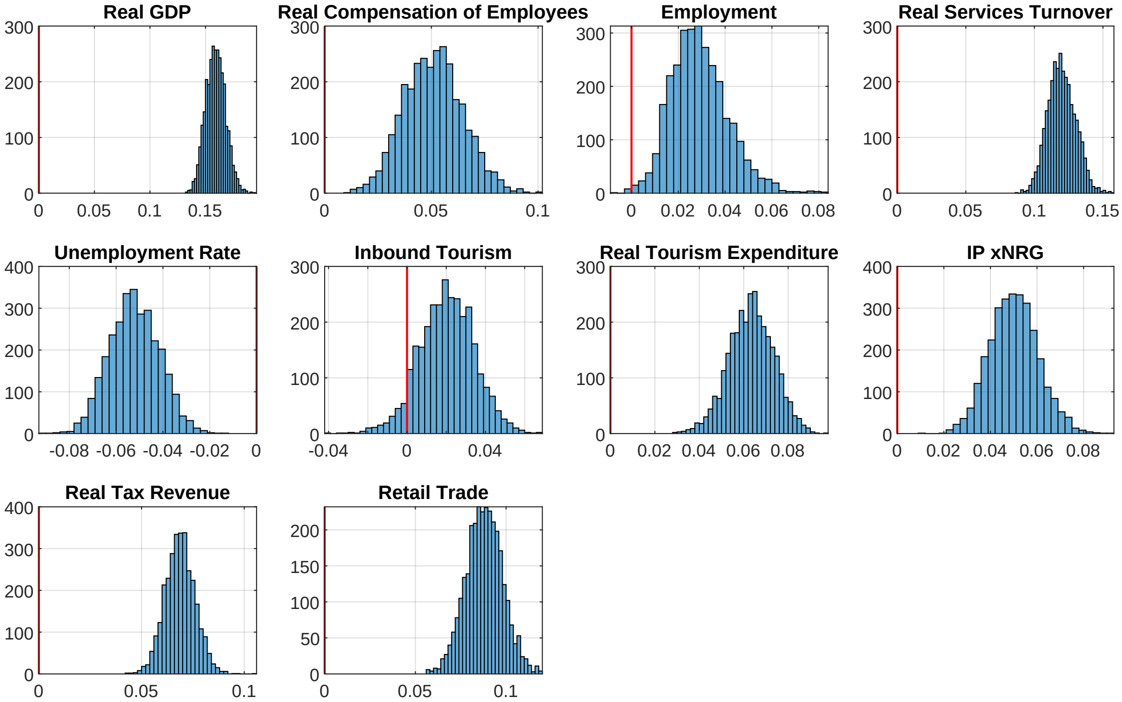
Notes: The x-axis represents time while the y-axis the value of the New BCI and its contributions from the categories.

We provide more information on the importance of each series in the dataset to the overall index. Indeed, Figures 3 to 6 show the posterior distributions of the factor loadings for the variables, sorted by category. As all the variables are standardised before estimation, the factor loadings can be compared with one another to provide an indication of how strongly the underlying variables contribute to the index. A zero vertical line is displayed in red to evaluate how significant each factor loading is.[18]

Figure 3 presents the posterior distributions relative to the factor loadings associated with the variables belonging to the real activity category. All variables present a positive loading, with the obvious exception of the unemployment rate. For example, growth in real GDP positively contributes to business conditions, while a higher unemployment rate is associated with a deterioration of the index. Furthermore, higher inbound tourism and tourism expenditure are related with a positive effect on economic conditions. Notably, the main contributors in this category are real GDP and real services turnover, with factor loadings centred around 0.16 and 0.12, respectively.

[18]It is important to emphasise that the factor loadings presented here do not imply any causality relationship going from the variables to the index. Information about their median values is reported in Table B.1 in Appendix B.4. In addition, Table B.2 in Appendix B.5 reports the variance share of the common factor f_t, indicating the proportion of the unconditional variance of each series in the dataset that is explained by the common factor.

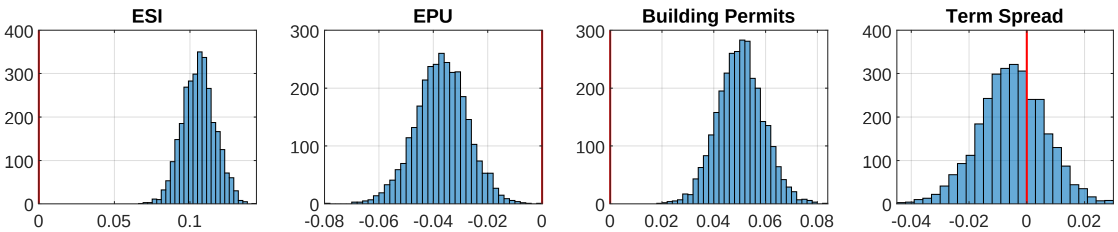
Figure 3: Posterior distributions of the factor loadings relative to the variables belonging to the real activity category.



Source: Authors' calculations.
Notes: The x-axis shows the magnitude of the factor loading, while the y-axis the number of posterior draws.

Figure 4 shows the factor loadings relative to the expectations category. Both the ESI and building permits contribute positively to the New BCI, while the EPU is negatively related to it. On the one hand, higher expectations about future economic activity translate into better business conditions, while a higher EPU reflects greater economic policy uncertainty, which undermines proper long-term planning and, consequently, worsens economic conditions. Notably, the ESI's factor loading is centred around 0.11, making it particularly relevant when compared with the main variables driving the real activity category. In contrast, the term spread exhibits a factor loading whose mode lies in negative territory, although its overall contribution appears to be indistinguishable from zero.

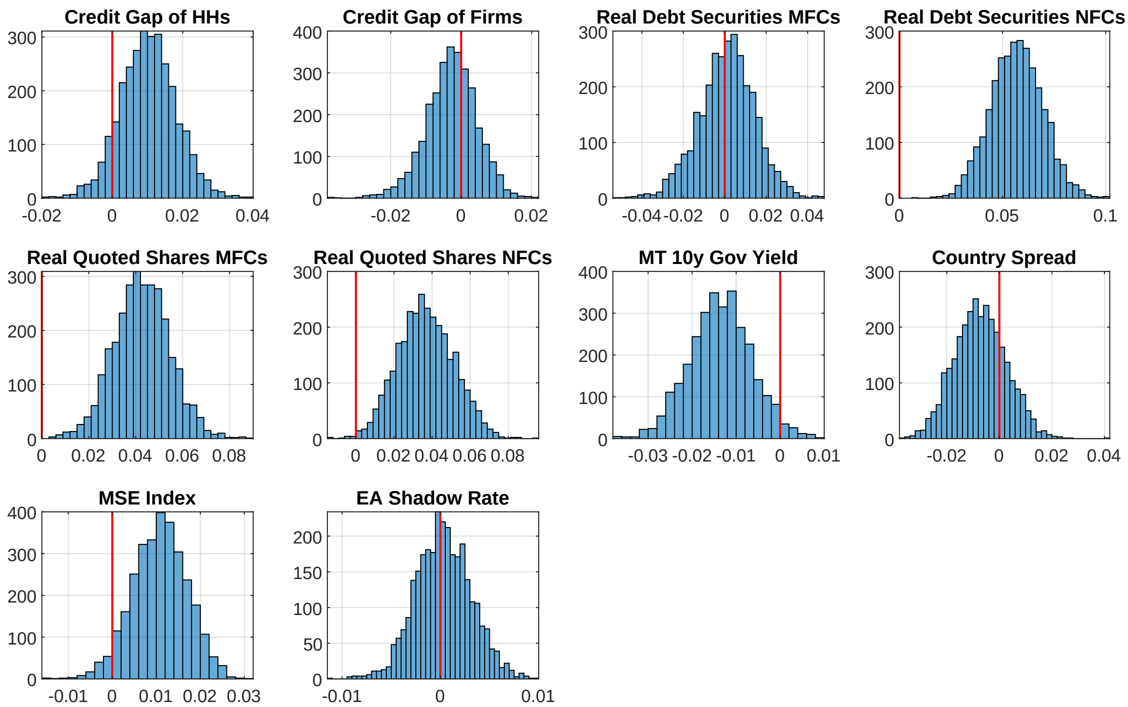
Figure 4: Posterior distributions of the factor loadings relative to the variables belonging to the expectations category.



Source: Authors' calculations.
Notes: The x-axis shows the magnitude of the factor loading, while the y-axis the number of posterior draws.

In the financial conditions category, shown in Figure 5, the credit gap relative to households, real debt securities of NFCs, and real quoted shares for both MFCs and NFCs appear to contribute positively to the index. Households seem to rely on credit, likely to finance the purchase of their properties, whereas firms do not appear to depend as heavily on bank credit to support their activity. Similarly, MFCs do not appear to rely on debt securities as much as NFCs.[19] We also find that the 10-year Maltese bond yield and the country spread are negatively related to the index, while, not surprisingly, the MSE index contributes positively. Higher long-term bond yield and country spread impact negatively business conditions, as they convey economic agents' expectations of worsening future conditions in the country. Interestingly, the shadow rate for the euro area exhibits a factor loading closely centred around zero.

Figure 5: Posterior distributions of the factor loadings relative to the variables belonging to the financial conditions category.



Source: Authors' calculations.

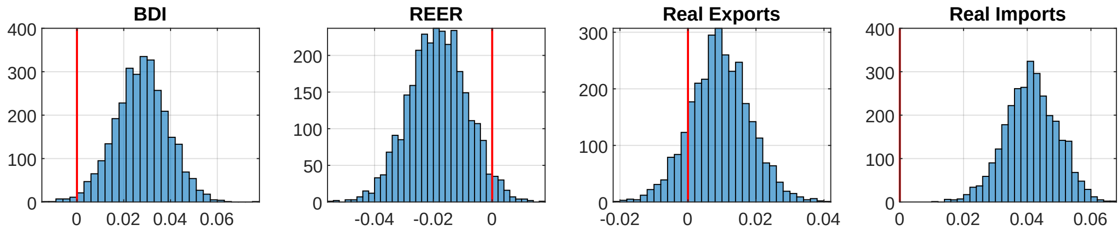
Notes: The x-axis shows the magnitude of the factor loading, while the y-axis the number of posterior draws.

Finally, for the international trade category, Figure 6 displays how real exports, real imports, and the BDI are positively related to the index. In contrast, the REER is not, as an increase in the latter would indicate a deteriorating competitiveness of the country. Interestingly, imports appear to be more relevant than exports in explaining fluctuations in Maltese business conditions, with factor loadings showing a mode of around 0.04 and 0.01, respectively. This likely reflects the strong dependence of imports on domestic demand, while exports are influenced by a combination of domestic supply capacity and

[19]Firms' low reliance on bank credit is consistent with the results outlined in the Central Bank of Malta's Business Dialogue. The survey finds that self-financing dominates among Maltese firms.

foreign demand conditions.

Figure 6: Posterior distributions of the factor loadings relative to the variables belonging to the international trade category.



Source: Authors' calculations.

Notes: The x-axis shows the magnitude of the factor loading, while the y-axis the number of posterior draws.

The analysis provided on the basis of Figures 3 to 6 demonstrates that multiple variables significantly contribute to the New BCI, as their factor loadings exhibit posterior distributions largely distinct from zero. Although the most relevant factors belong to the real activity category, developments in the index are not driven solely by a handful of variables but rather are based on a broader set of information.

4.2 Comparison with the BCI currently adopted by the Central Bank of Malta and Real GDP growth

Comparing the New BCI with the current index used by the Central Bank of Malta is crucial to evaluate how the former performs in detecting the evolution of the Maltese economic conditions vis-à-vis its existing version. In this regard, from a policy institution's standpoint, it is imperative to ensure that the public is provided with a comparable narrative on the country's state of the economy, independently of the index used. Figure 7 shows the two indices for the period going from January 2001 to February 2026. Notably, the New BCI is transformed into monthly frequency to make it comparable with the current one and to make it consistent with the frequency at which the Central Bank of Malta communicates the latter to the public.[20]

The derivation of both indices is based on DFM frameworks yielding standardised measures of business conditions. As a result, in the case of the Current BCI and similarly to the new index, zero corresponds to average economic conditions, while positive (negative) values indicate above- (below-) average conditions.[21] To facilitate the comparison between the two, the green shaded areas in Figure 7 represent the months when both

[20] The New BCI is first estimated in its weekly form and then aggregated into monthly frequency, by averaging weekly observations.

[21] The new index adopts a DFM estimated in a Bayesian fashion, while the current one makes use of a DFM in a frequentist setting. Differently from the new one, the Current BCI's estimation is based on a dataset of nine variables, being, real GDP, tax revenue, industrial production, credit, ESI, inbound tourism, unemployment rate, term spread, and building permits. In its original version (2016), the Current BCI had a daily, weekly, monthly and quarterly data aggregating matrix which was simplified for operational reasons in 2020. In line with Aruoba et al. (2009) the index is standardised and normalised to a value of one over the estimated period. Please refer to Ellul (2016, 2020) for further information on the data and model.

indices detect a similar state of the economy, i.e., either above- or below-average conditions, while the red shaded areas represent periods when the two indicators disagree.

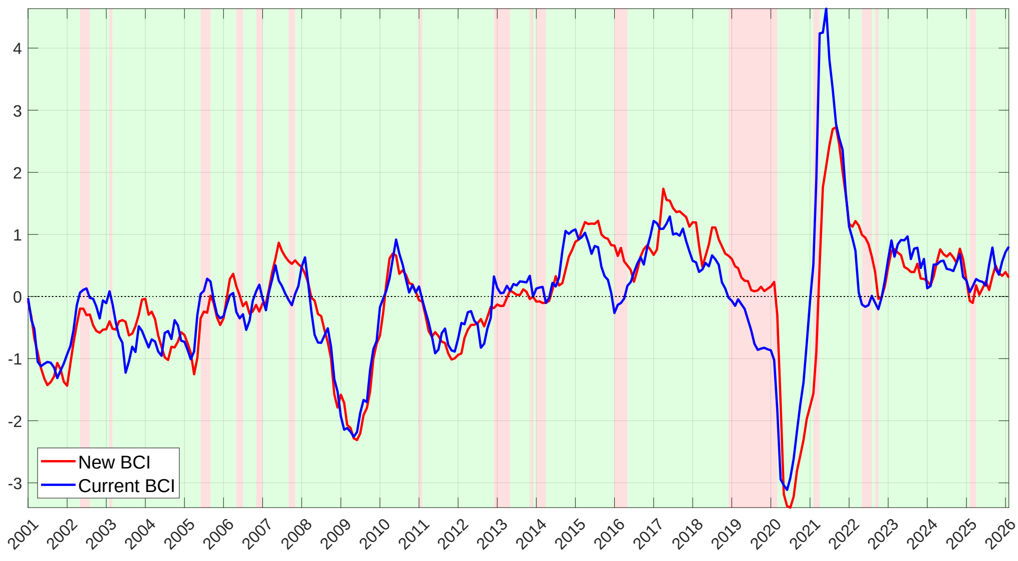
Overall, the two indices move closely together, with sporadic instances of disagreement. As reported in Table 2, the correlation between the two is 0.84, they provide a similar assessment of the state of the economy in 83.4% of the months considered, while their mean absolute distance (MAD) is equal to 0.37.

Table 2: Statistics between New and Current BCIs at monthly frequency.

Correlation	Agreement	MAD
0.84	83.4%	0.37

Figure 7 clearly demonstrates how the most noticeable differences emerge when assessing business conditions around the COVID-19 period. The Current BCI appears to move into negative territory well before the one developed in this paper, respectively, in December 2018 and March 2020. This might be partly explained by the ESI playing a heavier role in the estimation of the Current BCI, implying that the expectations of worsening future conditions had already started to weigh on the index throughout 2019. Moreover, during the worst months of the pandemic, the Current BCI dips slightly less than the new one. When assessing the behaviour of the indices in relation to the recovery from the pandemic in mid-2021, the New BCI depicts a rebound that is less strong than that of the Current BCI. Finally, the two indices present negligible differences throughout 2024, 2025, and 2026, thereby providing comparable information on the recent state of the economy, as the latter appears to move towards more average conditions following the strong post-pandemic rebound in economic activity.

Figure 7: The New and Current Business Conditions Indices at a monthly frequency (red and blue solid lines, respectively).



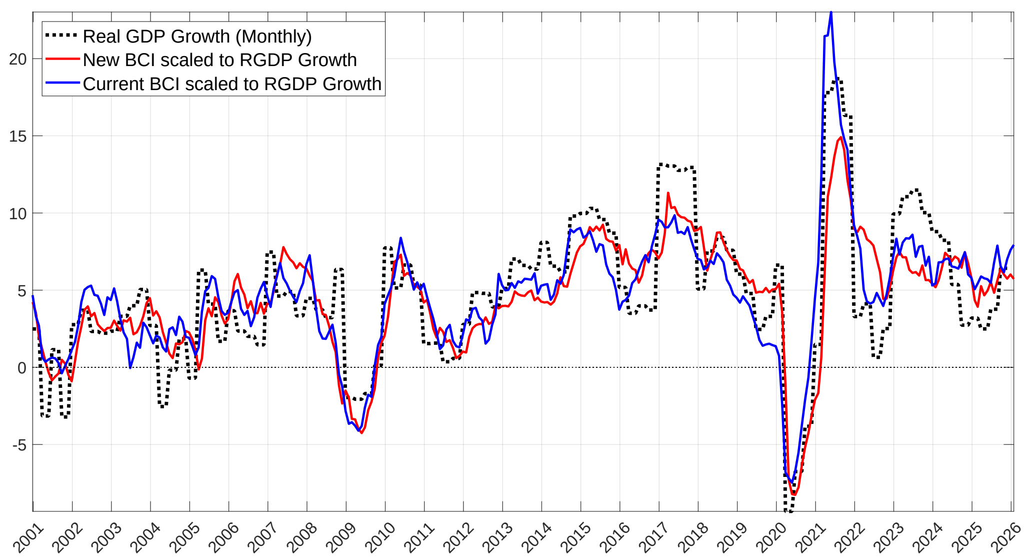
Source: Authors' calculations.

Notes: The x-axis represents time while the y-axis the value of the New and the Current BCIs. The shaded areas indicate periods in which both indices assume the same (green) or opposite sign (red).

Although not being the primary objective for developing the New BCI in this paper, understanding how it performs in tracking real GDP growth is undoubtedly a relevant feature to explore from a policy institution's standpoint.[22]

Figure 8 depicts Malta's real GDP growth, converted into monthly observations, plotted with the New and the Current BCIs, properly scaled to this key indicator of economic activity.[23] A graphical inspection suggests that the BCIs closely move with GDP, with periods of subdued activity and their associated recoveries captured in a timely manner. Moreover, the direction and magnitude of the fluctuations in the indicators appear to be broadly comparable to those observed in GDP growth.[24]

Figure 8: The New and Current Business Conditions Indices scaled to Maltese real GDP growth (red and blue solid lines, respectively) and the real GDP growth at a monthly frequency (black dotted line).



Source: Authors' calculations.

Notes: The x-axis represents time while the y-axis the value of the Maltese real GDP growth and the scaled New and Current BCIs.

4.3 Stability across data vintages

The Central Bank of Malta is one of the major providers of economic analysis and research in the country and, in its output, it regularly informs the public about the conditions of the Maltese economy. One of the main channels adopted is the publication

[22]The recent literature includes some studies performing similar analyses see, for example, Eraslan and Götz (2020), Lewis et al. (2022), ING Research (2021), and Bańbura et al. (2024).

[23]Monthly observations of real GDP growth in Figure 8 are obtained by repeating its quarterly value over the months of the reference quarter. This interpolation is done solely for illustrative purposes and plays no role in the estimation. As a quarterly-frequency variable, real GDP enters the model with weekly, and hence monthly, observations treated as missing which are estimated by means of the Carter and Kohn (1994) algorithm.

[24]The correlation between real GDP growth and the New BCI is 0.80, compared with 0.83 for the current one. This modest increase is unsurprising, as the existing indicator is constructed from a smaller dataset and is more heavily influenced by real GDP dynamics, which mechanically strengthens its contemporaneous association with GDP.

of its monthly Economic Update, which provides an overview of recent economic developments. In its reporting of several macroeconomic indicators, the Bank also presents an overall assessment of the economy via the Current BCI.

As a policy institution communicating regularly to the public, the Central Bank of Malta aims at maintaining a narrative that remains consistent over time and is minimally subject to revisions. However, this task poses a major challenge when relying on composite indicators of business conditions such as the Current BCI. Notably, in each monthly communication, the latter might present changes in its historical values as new data vintages are used in its computation.

Normally, three are the reasons behind such changes, namely being: the inclusion of new observations, the revisions of past data, and the smoothing techniques typically involved in the estimation of composite indicators based on DFMs. The addition of new data provides new information on recent developments in business conditions. However, given the ragged-edge nature of the datasets involved in the estimation of such indicators, the latter are likely to be influenced, particularly in their most recent values. Meanwhile, revisions to the underlying macroeconomic series can lead to significant changes in the historical values of composite indicators, especially if most variables included in the dataset are subject to periodic revisions. Finally, smoothing techniques introduce an additional layer of uncertainty into the estimation of the indicator throughout the time dimension covered by the sample.

Maltese National Accounts Data are traditionally subject to substantial revisions (Grech, 2018; Debono, 2024), which can have important implications on the computation of both the Current and the New BCIs. One of the key variables in the index is GDP, which is not new to sharp revisions. An emblematic example is given by the recent benchmark revision in national accounts data that was implemented in August 2024, in conjunction with the release of the real GDP figures relative to the second quarter of that year.[25] Such a large-scale revision affected the whole sample period covered by the specific vintage, and especially revised upwards values relative to 2020 and downwards values relative to 2022.[26]

The left panel in Figure 9 displays how the historical values of the Current BCI have changed as a result of the estimation done with the data vintage collected as of August 2024 vis-à-vis the one based on data collected as of May 2024, the latter being the vintage pertaining to the release of national accounts data for the first quarter of

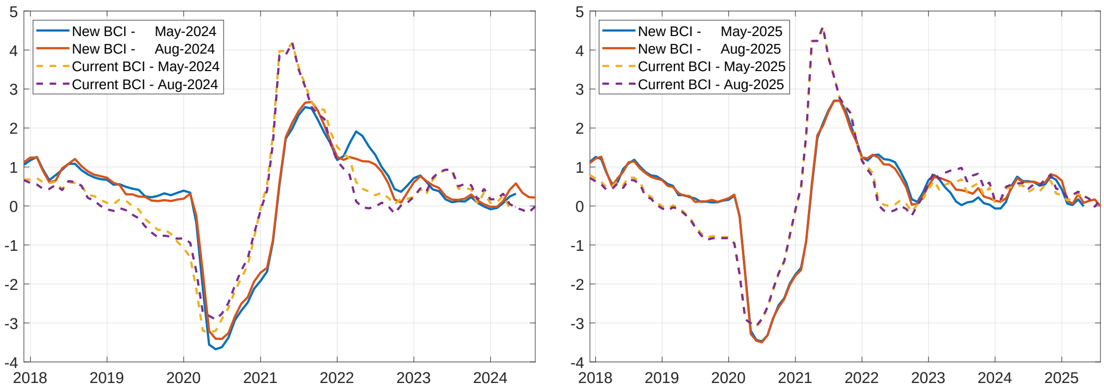
[25] The Maltese National Statistics Office (NSO) issued a notice with regards to the GDP benchmark revision of August 2024, highlighting the main changes in the data, please refer to the link: NSO Information Notice. It is important to note that data revisions may not solely be due to routine revisions, but may also be affected by other *major* revisions which can be further classified as either; *ad hoc* revisions, or periodical *benchmark* revisions. The former are done to conform with methodological changes or changes in classifications, while the latter pertain to changes in data sources or estimation techniques. Major revisions are implemented to ensure historical consistency with the new definitions and/or methodologies in place (Debono, 2024). Further details can be found as follows: National Accounts Benchmark Revision 2020.

[26] In the benchmark revision of August 2024, annual real GDP growth was revised upwards from -8.0% to -3.3% for 2020 and downwards from 8.1% to 4.2% for 2022.

2024. As a comparison, a similar estimation for the New BCI is reported.[27] Noticeable changes in both indices are evident in conjunction with the aforementioned revisions in real GDP, and in real compensation of employees for the New BCI. Specifically, for both BCIs, the trough experienced in 2020 was less severe than what could be inferred by the resulting estimation from data vintage for May 2024. In contrast, the economic recovery experienced in 2022 was less robust than that suggested by the indicators estimated with the previous data vintage.

In the right panel of Figure 9 we present a similar analysis conducted using data vintages collected for August 2025 and May 2025. This comparison serves a different purpose from that of the August 2024 exercise. While the latter captures the effect of a major benchmark revision, the former allows us to assess whether the revisions associated with the regular incorporation of newly available information materially alter the historical profile of the BCIs once the benchmark methodology is held unchanged. Specifically, in August 2025 the national accounts vintage for the second quarter was released and downward revisions for 2022 and upward revisions for 2023 were implemented.[28] The most evident changes in both BCIs are reflected in 2023, suggesting more favourable business conditions than previously detected. Meanwhile, minimal changes are observed in the remaining historical values of the two indices.

Figure 9: The New and Current Business Conditions Indices across the vintages available as of the end of May and August 2024 (left panel), and as of the end of May and August 2025 (right panel).



Source: Authors' calculations.

Notes: The x-axis represents time while the y-axis the value of the New and the Current BCIs.

All in all, despite the considerable scale of the revisions in the underlying data, both New and Current BCI measures seem to be fairly stable and retain most of the qualitative implications, even when re-estimated with a new vintage.

Nevertheless, the examples shown in Figure 9 still raise the necessity to rigorously investigate which of the two BCIs is more prone to be affected by data revisions. There-

[27]Please refer to Tables A.2 and A.3 in Appendix A.3 for a description of the data available in the estimation of the BCIs for this exercise.

[28]With respect to May 2025, in August 2025, annual real GDP growth was revised downwards from 4.3% to 2.5% for 2022 and upwards from 6.8% to 10.6% for 2023.

fore, to formally assess how stable the two indicators are across various data vintages, we implement the following exercise. We compile real-time data vintages for the estimation of both BCIs coinciding with the quarterly releases of national accounts data, taking place at the end of February, May, August and November.[29] Specifically, we collect a total of twelve vintages compiled every three months between May 2023 and February 2026 and covering national accounts data releases pertaining to the first quarter of 2023 up to the last quarter of 2025.[30] Subsequently, we estimate both indices and compute a summary measure of their stability over time. More precisely, in a similar spirit to Lewis et al. (2022), we calculate a measure of root mean squared deviation (RMSD) for each pair of two consecutive vintages, i.e., between May 2023 and August 2023, August 2023 and November 2023, and so on, up to November 2025 and February 2026.[31]

More formally, we compute our measure of RMSD as follows:

$$RMSD_{v,v-1} = \sqrt{\frac{\sum_{t=1}^{T_{v,v-1}} (BCI_{t|v} - BCI_{t|v-1})^2}{T_{v,v-1}}} \tag{6}$$

for $BCI = New\,BCI, Current\,BCI$. In Equation (6) v denotes the data vintage available for a specific quarter, while $v-1$ refers to the preceding one. $BCI_{t|v}$ represents the value of either the new or the current indicator at time t, estimated on the basis of the information provided by vintage v. Finally, $T_{v,v-1}$ represents the number of months for which data are concurrently available in both vintages v and $v-1$.[32]

Table 3 shows the results of this analysis.[33] The second and third columns show the values associated with the two indicators, while the fourth shows the relative RMSD, calculated as the ratio between the RMSDs of the New and the Current BCIs, respectively. Moreover, the last row provides a broader value covering all the vintage pairs together.[34] The RMSDs of the New BCI are typically lower than those associated with

[29] For the BCI proposed in this paper, some challenges arose when recreating the real-time datasets as past versions of some variables were no longer available at the time of compilation, e.g., quoted shares and debt securities. Conversely, for the Bank's current BCI all the data were available in real-time as they are regularly compiled on a monthly basis to be used for the Bank's publications. Finally, it is also worth noting that there are variables that do not experience revisions, such as building permits and interest rates pertaining to the 10-year Maltese bond yields, the country spread, and the term spread.

[30] Please refer to Tables A.2 and A.3 in Appendix A.3 for details on the data involved in this exercise.

[31] For ease of comparison, we carry out this analysis by using the two indicators expressed at a monthly frequency. Figure B.9 in Appendix B.6 depicts the estimates of each of the two versions of the BCI for the twelve vintages, with the current version shown in the left panel, while the new version is shown in the right panel. The evolution of the two indicators over time illustrates how they function operationally as new information becomes available.

[32] By means of this analysis, we aim to provide an overall assessment of the extent to which the two BCIs exhibit changes in their respective historical values over time. As such, we do not attempt to disentangle the specific contributions of new data, data revisions, and smoothing techniques to such changes. Although these factors are relevant, analysing them lies beyond the scope of this paper and is therefore left for future research.

[33] Given the limited number of vintages, a formal test of the statistical significance of differences in RMSD cannot be reliably conducted.

[34] The overall RMSD is calculated by appending all the squared variations stemming from each of the

the Current BCI. The highest deviation for the New BCI is recorded for the May 2024 to August 2024 vintage pair, while for the Current BCI it is recorded for the August 2024 to November 2024 vintage pair, standing at 0.12 and 0.17, respectively.[35] On the other hand, the lowest deviation for the New BCI is 0.03, which is recorded multiple times. Meanwhile, for the Current BCI the lowest deviation is recorded for the August 2025 to November 2025 vintage pair, standing at 0.02. Finally, while the New BCI is found to have an overall RMSD of 0.05, the current one exhibits a higher value, standing at 0.09, hinting that it is more likely to change its historical values with new vintages. In fact, in light of the overall relative RMSD, the New BCI appears to be 40% less volatile than the version currently used by the Central Bank of Malta. The higher stability demonstrated by the New BCI is not unexpected as, compared with the current version, it relies on a broader set of indicators, thereby significantly reducing the likelihood that a substantial portion of the dataset is revised at the time of estimation.[36]

Table 3: Root mean squared deviations, across vintage pairs and overall.

	RMSD		
Vintage pair	New BCI	Current BCI	Relative
May 2023 - Aug 2023	0.03	0.05	0.63
Aug 2023 - Nov 2023	0.03	0.09	0.35
Nov 2023 - Feb 2024	0.03	0.07	0.43
Feb 2024 - May 2024	0.03	0.08	0.43
May 2024 - Aug 2024	0.12	0.13	0.93
Aug 2024 - Nov 2024	0.05	0.17	0.32
Nov 2024 - Feb 2025	0.03	0.09	0.30
Feb 2025 - May 2025	0.03	0.03	1.01
May 2025 - Aug 2025	0.07	0.07	0.91
Aug 2025 - Nov 2025	0.04	0.02	2.33
Nov 2025 - Feb 2026	0.04	0.05	0.71
Overall	0.05	0.09	0.60

Source: Authors' calculations.
Note: The relative RMSD is calculated as the ratio between the RMSDs of the New and the Current BCIs, respectively. Figures were rounded to two decimal places and minor rounding discrepancies may occur.

vintage pairs.

[35] Contrary to expectations, the highest RMSD for the Current BCI is found for the vintage pair of August 2024 to November 2024, rather than for May 2024 to August 2024. After a careful investigation, we found that there were substantial revisions in some other variables specific to the current BCI's dataset for November 2024, e.g., credit.

[36] A one-off instance where the New BCI holds a higher RMSD occurs for the vintage pair of August to November 2025. A possible reason for this could be a higher volatility of variables that are not common between the two indices. For example, retail trade, a relatively important contributor in the New BCI as previously reflected by its posterior distribution in Figure 3 and Table B.1 as well as its variance share in Table B.2, appears to be relatively volatile during the end of 2024 and 2025, as displayed in Figure B.5 in Appendix B.3.

5 Conclusion

In this paper, we develop a new indicator of business conditions that is motivated by the rapid pace of economic developments during the pandemic and the ensuing recovery, and by the necessity to overcome the limitations present in the BCI currently employed by the Central Bank of Malta. Compared with the latter, we adopt a larger and more diversified dataset, making use of variables that more closely reflect the various aspects of the Maltese economy. From a methodological point of view, we adopt a mixed-frequency DFM handling weekly, monthly, and quarterly observations, as developed in Baumeister et al. (2024) and further employed in Bańbura et al. (2024).

The New BCI is able to properly capture Malta's economic conditions over time and to provide a decomposition of the driving forces behind its fluctuations, grouped into four categories. Among these, the real activity one represents the largest contributor to the developments of the index. Moreover, the model underlying the estimation of the New BCI allows to disentangle the contributions of the individual variables, thereby enhancing the interpretability of the index. In particular, the model indicates that the main variables driving the fluctuations of the real activity category are real GDP and real services turnover, while retail trade and real tourism expenditure contribute to a slightly lesser extent. Furthermore, the ESI plays a relevant role in driving the expectations category, which represents the second most important contributor.

When comparing the new index with the Bank's Current BCI, the analysis shows that the two move closely together, with slightly noticeable differences emerging around the pandemic period. Additionally, we compare the two indices with the growth rate of real GDP. The dynamics of the indicators appear broadly consistent with changes in real GDP growth, thereby underscoring their relevance from the perspective of a policy institution. Finally, we demonstrate that the New BCI is more robust to data revisions than the Current BCI. An assessment of the stability of the two indices across data vintages indicates that the New BCI is less sensitive to the incorporation of newly available information, exhibiting smaller changes in its values as the underlying data are revised.

Although the ability to track overall economic conditions in a timely manner is the main objective of the New BCI, both the indicator and the econometric framework employed for its construction can be used to expand the research and modelling capabilities of the Bank. Specifically, the New BCI can additionally be used to conduct structural analysis to understand how the Maltese economy reacts in a high-frequency setting, which is a desirable feature in a fast-changing world. Furthermore, the mixed-frequency DFM can be used to develop indicators that focus on other segments of the economy or to conduct nowcasting and forecasting activities.

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Appendix A Data

A.1 Sources and information

Real activity
We use data on real GDP from 2000 up to the fourth quarter of 2025. In this regard, the vintage used relates to the NSO news release 033/2026, with the whole series being sent to us by NSO. With regards to real services turnover, we utilise the short-term business statistics available from NSO. In this case, the Services Turnover Indicator (for NACEs G to N excluding K, as per NACE Rev.2) is taken and is then deflated by the HICP index pertaining to Services, which is obtained from Eurostat.[37] For industrial production, we take the unadjusted series from Eurostat on production in industry excluding MIG energy. Real tax revenue is calculated by summing the monthly tax revenue (cash definition) and deflating it by the HICP. Finally, the monthly unadjusted volume of sales indicator for retail trade, except for motor vehicles and motorcycles, is added. It can be noted that these variables are available from 2000.

The quarterly real compensation of employees is calculated by deflating the nominal compensation of employees in millions of national currency by the GDP deflator. These are taken from the national accounts database on Eurostat. Furthermore, total employment figures are taken from Eurostat's national accounts database, while unemployment figures are extracted from the European Commission's database. Data is available from 2000.

Monthly inbound tourism figures, excluding cruise ship passengers, are taken from the NSO. Furthermore, monthly real tourism expenditure is calculated by deflating the nominal tourism expenditure, taken from the NSO, by the monthly index of HICP, sourced from Eurostat. The data for tourism figures starts from January of 2000 and while that of expenditure starts from January of 2001.

Expectations
The ESI is taken from the European Comission database on survey-based indicators. This data is already seasonally adjusted and is available from November 2002 onwards. Data for building permits is obtained from the Planning Authority and is available from January 2005. The EPU index is extracted from the CBM and is available from January 2004. Moreover, in order to calculate the term spread both rates are sourced from the CBM. These quasi-daily calculations are transformed into weekly observations by transforming them in EViews. This data is available on a weekly basis from January 2002.

Financial conditions
Data on the semi-structural credit gap for households and for firms is obtained from estimates by the CBM and included in this category. These are derived using a multivariate filter and are informed by developments across the macro-economy (Gatt, 2024). These

[37] Refer to: National Statistics Office Malta, released 23/02/2026, NR029/2026: Short-term Services Indicators: Q4/2025 for an explanation of the methodology used to compile this indicator.

are available from the first quarter of 2000. Data on issues of debt securities and quoted shares for financial and non-financial corporations is available from the first quarter of 2004. To work out the real values, nominal data is sourced from the CBM and then deflated by the GDP deflator.

The rates used for the country spread are both obtained from Eurostat and are available from January 2000. The MSE index is obtained from the MSE website, while data on the EA shadow rate is obtained from the Krippner macro-finance analysis website. These two variables are transformed into weekly observations using Matlab and are available from the first week of 2000.

International trade

The BDI is obtained from Bloomberg, while the REER is sourced from the Bank for International Settlements. These two variables are available from January 2000. Turning to real exports and real imports, these are worked out as the nominal exports and imports of goods less exports and imports of Petroleum, petroleum products and related materials and Other transport equipment. These are then deflated by the Unit Value Index for exports and imports, respectively, which serves as a measure of price changes of exports and imports. This data is obtained from Eurostat and is available from January of 2002.

A.2 Stationarity checks

This appendix presents stationarity checks relative to each of the variables included in the model described in Section 3. The analysis is performed on the transformed and standardised series, and is carried out in two steps. The first step makes use of the traditional Augmented Dickey-Fuller (ADF) test developed in Dickey and Fuller (1979, 1981), while the second step complements with the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) stationarity test developed in Kwiatkowski et al. (1992). Table A.1 presents the results where the stationarity properties are evaluated at the 5% significance level. Rather than reporting the test statistics, the table indicates whether each test suggests the presence of stationarity. The corresponding test statistics and associated p-values are available upon request.

Table A.1: Stationarity tests relative to the variables included in the dataset for Malta: ADF and KPSS.

Category	Variable	Transformation	Frequency	Stationarity	
				ADF	KPSS
Real Activity	Real GDP	Y-o-Y Growth	Q	✓	×
	Real Compensation of Employees	Y-o-Y Growth	Q	✓	×
	Employment	Y-o-Y Growth	Q	✓	×
	Real Services Turnover	Y-o-Y Growth	Q	✓	×
	Unemployment Rate	Annual difference	M	✓	✓
	Inbound Tourism	Y-o-Y Growth	M	✓	×
	Real Tourism Expenditure	Annual difference	M	✓	✓
	Industrial Production	Y-o-Y Growth	M	✓	✓
	Real Tax Revenue	Y-o-Y Growth	M	✓	✓
	Retail Trade	Y-o-Y Growth	M	✓	×
Expectations	ESI	Level	M	✓	×
	EPU	Level	M	✓	×
	Building Permits	Annual difference	M	✓	✓
	Term Spread	Annual difference	W	✓	✓
Financial Conditions	Household Credit Gap	Level	Q	✓	×
	Firm Credit Gap	Level	Q	✓	✓
	Real Debt Securities MFCs	Y-o-Y Growth	Q	✓	✓
	Real Debt Securities NFCs	Y-o-Y Growth	Q	✓	×
	Real Quoted Shares MFCs	Y-o-Y Growth	Q	✓	✓
	Real Quoted Shares NFCs	Y-o-Y Growth	Q	✓	✓
	Malta 10-year Gov Bond Yield	Annual difference	M	✓	✓
	Country Spread	Annual difference	M	✓	✓
	MSE Index	Y-o-Y Growth	W	✓	✓
	EA Shadow Rate	Annual difference	W	✓	×
International Trade	BDI	Annual difference	M	✓	✓
	REER	Annual difference	M	✓	✓
	Real Exports	Y-o-Y Growth	M	✓	✓
	Real Imports	Y-o-Y Growth	M	✓	✓

Source: Authors' calculations.

Notes: The stationarity tests are evaluated at a 5% significance level. As the variables were first transformed as described in Table 1 and subsequently standardised, the tests are conducted using specifications with no deterministic component (i.e., no intercept and no time trend). The lag lengths for the ADF tests are chosen using the Akaike Information Criterion (AIC) proposed by Akaike (1974). It is important to emphasise that ADF and KPSS test different null hypotheses which are, respectively, presence of unit roots and stationarity.

Table A.1 shows that all the transformed series are deemed stationary according to the ADF test, whereas the same conclusion cannot be drawn from the KPSS test. Specifically, the KPSS test rejects the null hypothesis of stationarity for a number of variables. Notable examples include Maltese real GDP, compensation of employees and employment. This result is not unexpected, as macroeconomic time series often exhibit structural breaks and/or slow-moving drifts, even after standard transformations such as year-on-year growth rates or differences. In the Maltese context, these features are likely related to the country's prolonged period of rapid economic expansion and the significant structural transformation of the economy over the past 15 years, which may have induced level shifts or changes in the underlying data-generating process. Moreover, the KPSS test is known to be sensitive to such features and may therefore over-reject the null hypothesis of stationarity in macroeconomic applications.

Finally, the relatively short sample available for the analysis, beginning in 2000, may further affect the finite-sample properties of both stationarity tests, reducing their power and contributing to conflicting inference. Taken together, the evidence from the ADF test, the standard transformations applied to the data, and the economic characteristics of the series suggest that the transformed variables are sufficiently stationary for the estimation of the dynamic factor model.

A.3 The New and Current BCIs: data availability across vintages

Table A.2: Current BCI: last observations available for vintages collected as of February, May, August and November.

	Vintage			
Variable	Feb	May	Aug	Nov
Real GDP	Q4(-1)	Q1	Q2	Q3
ESI	M02	M05	M08	M11
Term Spread	M02	M05	M08	M11
Credit	M01	M04	M07	M10
Inbound Tourism	M01	M04	M07	M10
Industrial Production	M01	M04	M07	M10
Tax Revenue	M01	M04	M07	M10
Unemployment Rate	M01	M04	M07	M10
Building Permits	M01	M04	M07	M10

Note: Q and M indicate quarters and months of the year in which the vintage is compiled, respectively. Q(-1) and M(-1) refer to quarterly and monthly data releases relative to the previous year.

Table A.3: New BCI: last observations available for vintages collected as of February, May, August and November.

	Vintage			
Variable	Feb	May	Aug	Nov
Real GDP	Q4(-1)	Q1	Q2	Q3
Real Compensation of Employees	Q4(-1)	Q1	Q2	Q3
Employment	Q4(-1)	Q1	Q2	Q3
Real Services Turnover	Q4(-1)	Q1	Q2	Q3
Unemployment Rate	M01	M04	M07	M10
Inbound Tourism	M01	M04	M07	M10
Real Tourism Expenditure	M01	M04	M07	M10
Industrial Production	M01	M04	M07	M10
Real Tax Revenue	M01	M04	M07	M10
Retail Trade	M01	M04	M07	M10
ESI	M02	M05	M08	M11
EPU	M02	M05	M08	M11
Building Permits	M01	M04	M07	M10
Term Spread	M02	M05	M08	M11
Household Credit Gap	Q4(-1)	Q1	Q2	Q3
Firm Credit Gap	Q4(-1)	Q1	Q2	Q3
Real Debt Securities MFCs	Q4(-1)	Q1	Q2	Q3
Real Debt Securities NFCs	Q4(-1)	Q1	Q2	Q3
Real Quoted Shares MFCs	Q4(-1)	Q1	Q2	Q3
Real Quoted Shares NFCs	Q4(-1)	Q1	Q2	Q3
Malta 10-year Gov Bond Yield	M02	M05	M08	M11
Country Spread	M02	M05	M08	M11
MSE Index	M02	M05	M08	M11
EA Shadow Rate	M02	M05	M08	M11
BDI	M02	M05	M08	M11
REER	M01	M04	M07	M10
Real Exports	M11(-1)	M02	M05	M08
Real Imports	M11(-1)	M02	M05	M08

Note: Q and M indicate quarters and months of the year in which the vintage is compiled, respectively. Q(-1) and M(-1) refer to quarterly and monthly data releases relative to the previous year. For Term Spread, MSE Index and EA Shadow Rate we collect weekly observations available till the end of the reference month. In addition, releases of real exports and imports data do not always occur with a four-month lag.

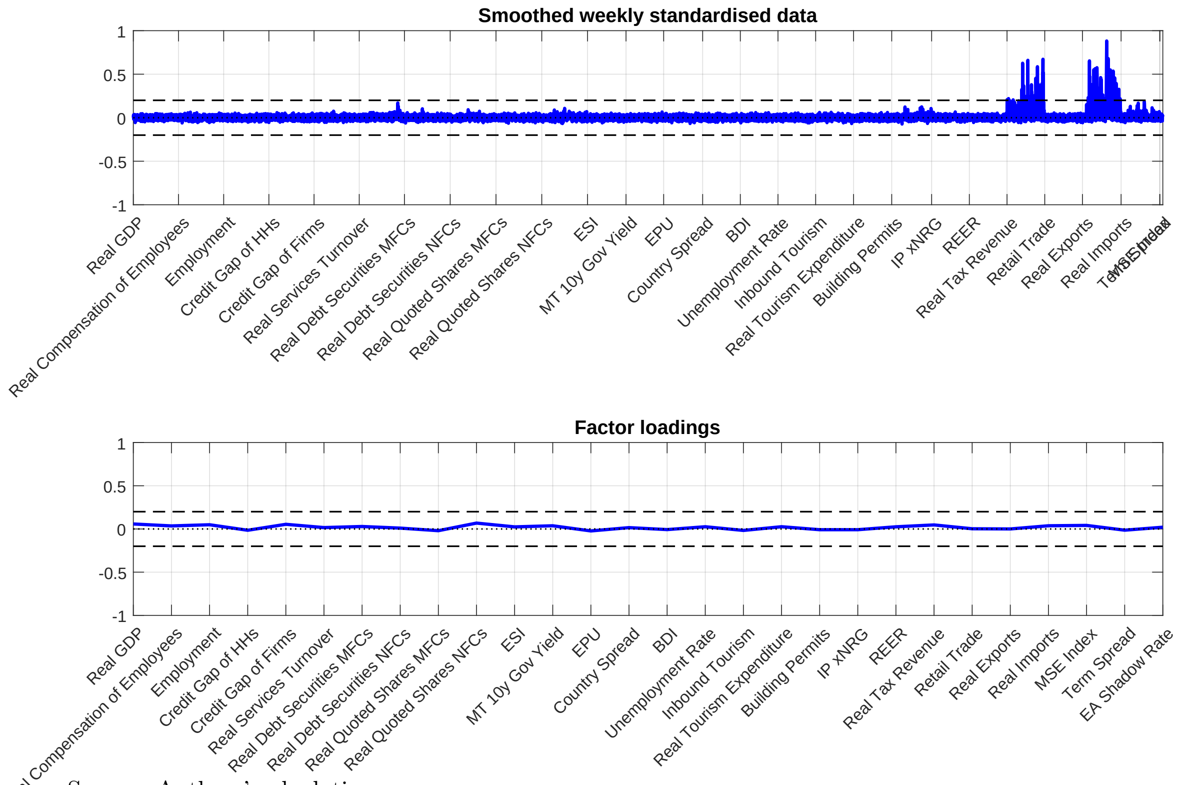
Appendix B Additional results

B.1 Convergence diagnostics

This appendix shows the convergence diagnostics relative to the model presented in Section 3. As suggested in Primiceri (2005), in order to assess the satisfactory performance of the algorithm, the 20^{th}-order autocorrelation of the retained draws is employed.

Figures B.1 to B.3 shows how most of the autocorrelations of the retained draws lie within the [0.2, 0.2] interval. Considering the high dimensionality of the model, the algorithm performs in a satisfactory way as most of the draws are nearly independent. As such, the latter can be used to conduct meaningful inference.

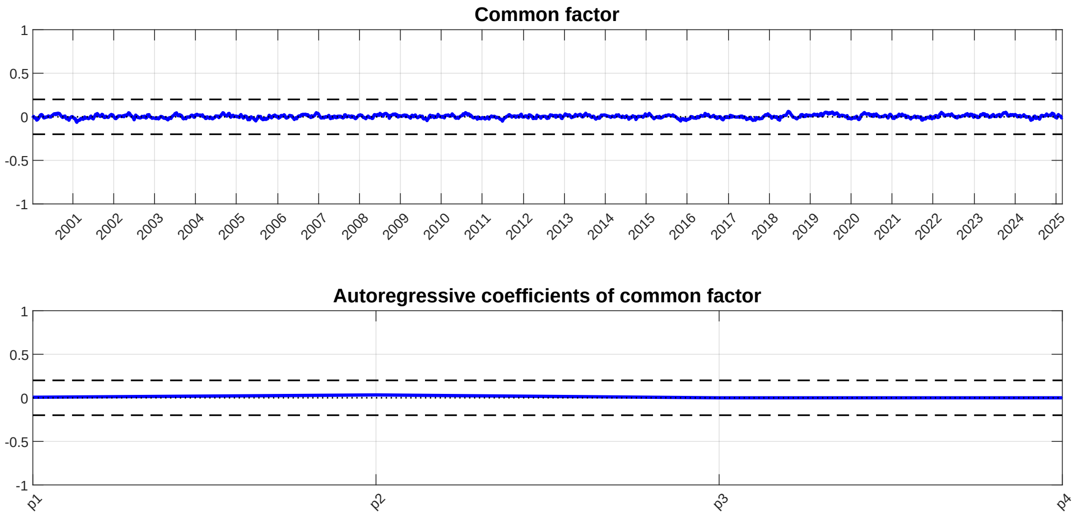
Figure B.1: 20^{th}-order autocorrelation of the retained draws: smoothed series (top panel) and factor loadings (bottom panel).



Source: Authors' calculations.

Notes: The y-axis shows the 20^{th}-order autocorrelation of the retained draws. The x-axis refers to the objects of interest that were estimated: weekly unobserved observations of the series in the dataset (upper panel) and factor loadings (bottom panel). The dashed horizontal lines represent the [0.2, 0.2] interval. The convergence diagnostics for the smoothed series are implied by those of the common factor, factor loadings, and idiosyncratic components. They are nevertheless reported here for the sake of transparency, as the smoothed series may be used in subsequent research.

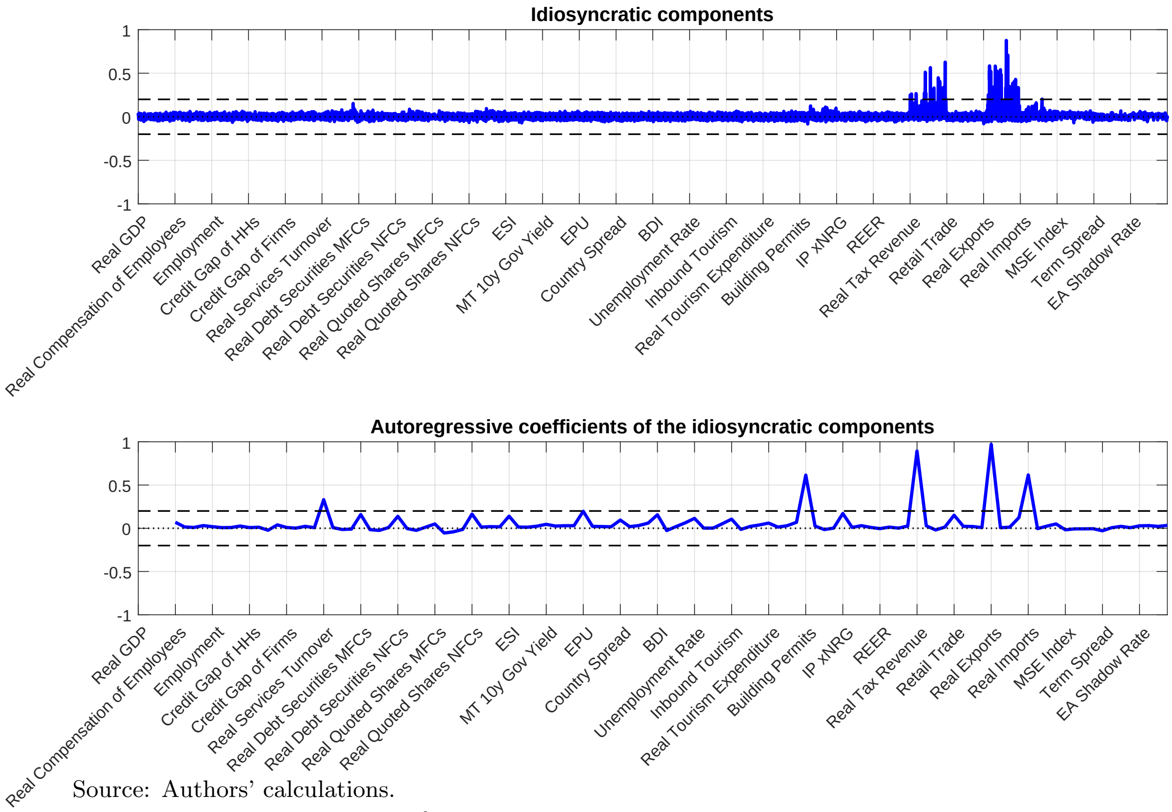
Figure B.2: 20^{th}-order autocorrelation of the retained draws: common factor (top panel) and its autoregressive coefficients (bottom panel).



Source: Authors' calculations.

Notes: The y-axis shows the 20^{th}-order autocorrelation of the retained draws. The x-axis refers to the objects of interest that were estimated: weekly values of the common factor (upper panel) and its four autoregressive coefficients (bottom panel). The dashed horizontal lines represent the [0.2, 0.2] interval.

Figure B.3: 20^{th}-order autocorrelation of the retained draws: idiosyncratic components (top panel) and their respective autoregressive coefficients (bottom panel).

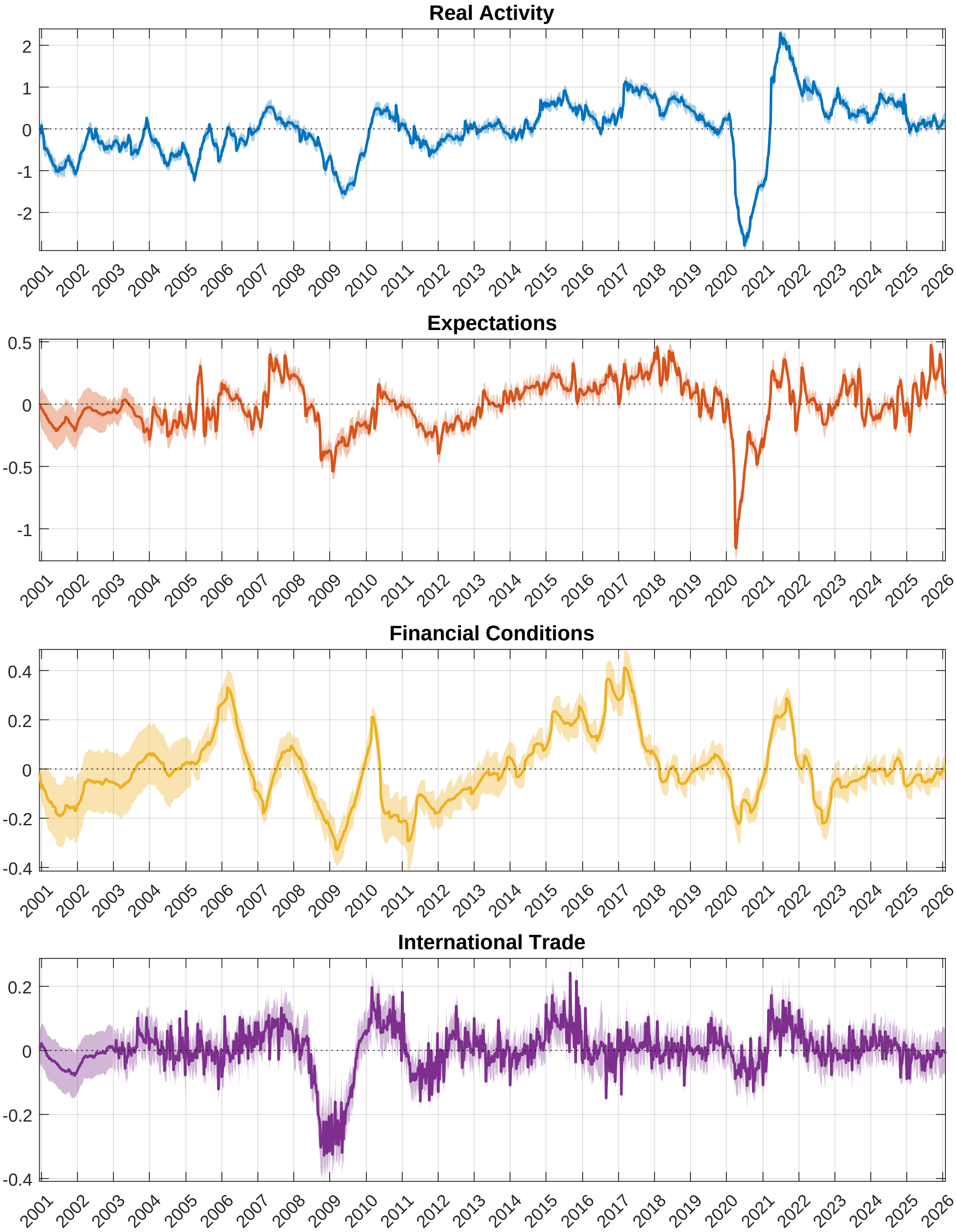


Source: Authors' calculations.

Notes: The y-axis shows the 20^{th}-order autocorrelation of the retained draws. The x-axis refers to the objects of interest that were estimated: weekly values of the idiosyncratic components (upper panel) and their four respective autoregressive coefficients (bottom panel). The dashed horizontal lines represent the [0.2, 0.2] interval.

B.2 Contributions from categories: median draws and credible regions

Figure B.4: Contributions from the four categories to the New BCI at a weekly frequency. Median draws (solid lines) and 68% credible regions (coloured shaded areas).

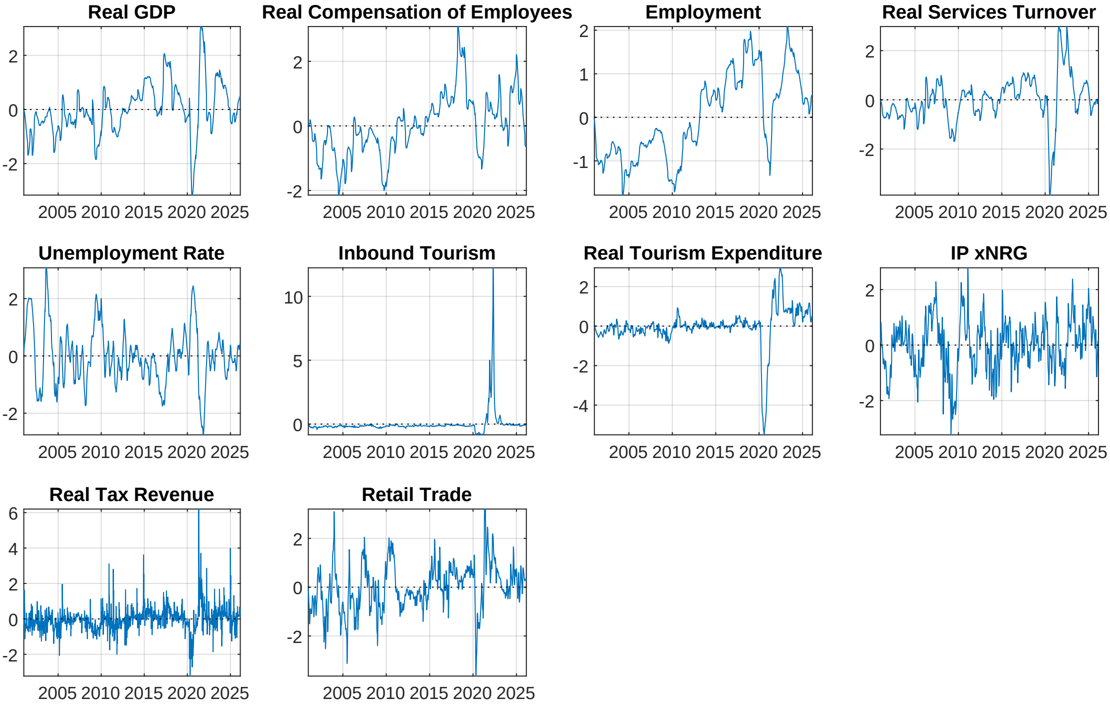


Source: Authors' calculations.

Notes: The x-axis represents time while the y-axis the median draws and the 68% credible regions.

B.3 Smoothed series

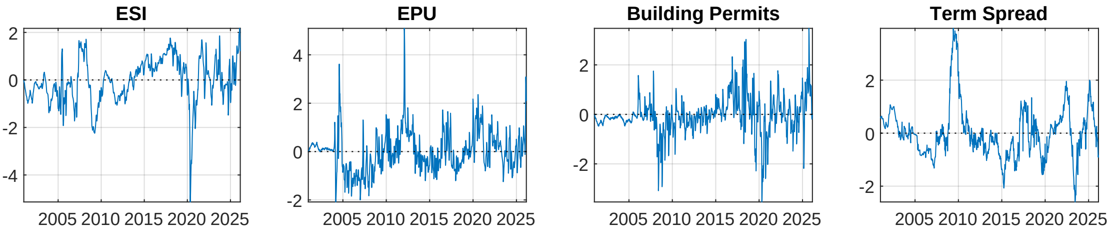
Figure B.5: Smoothed, standardised and transformed series for the real activity category: median values (blue lines).



Source: Authors' calculations.

Notes: The x-axis represents time while the y-axis the value of the smoothed, standardised and transformed series in each category.

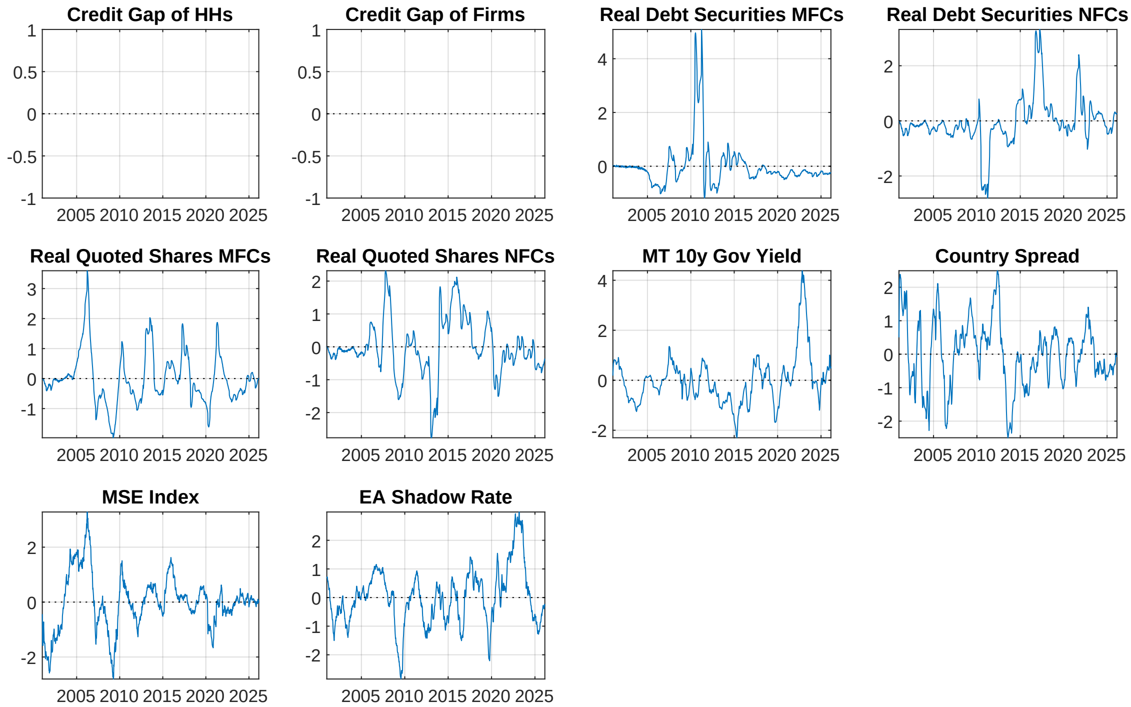
Figure B.6: Smoothed, standardised and transformed series for the expectations category: median values (blue lines).



Source: Authors' calculations.

Notes: The x-axis represents time while the y-axis the value of the smoothed, standardised and transformed series in each category.

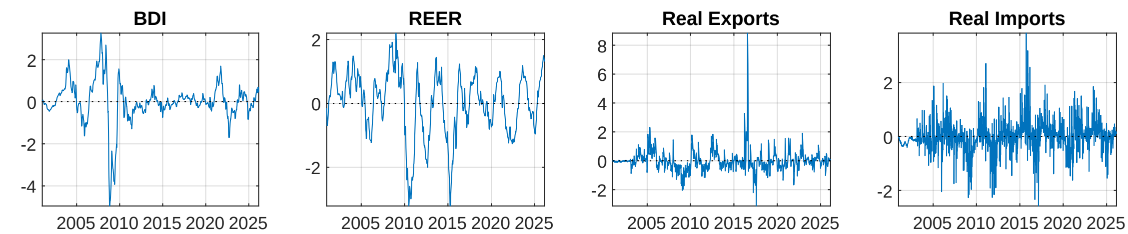
Figure B.7: Smoothed, standardised and transformed series for the financial conditions category: median values (blue lines).



Source: Authors' calculations.

Notes: The x-axis represents time while the y-axis the value of the smoothed, standardised and transformed series in each category. The smoothed series for the two credit gaps are not shown, as these data are not publicly available.

Figure B.8: Smoothed, standardised and transformed series for the international trade category: median values (blue lines).



Source: Authors' calculations.

Notes: The x-axis represents time while the y-axis the value of the smoothed, standardised and transformed series in each category.

B.4 Factor loadings: posterior medians and credible intervals

Table B.1: Factor loadings relative to the variables included in the dataset for Malta: posterior medians and 68% credible intervals.

Category	Variable	Frequency	Factor loading	
			Median	68% Interval
Real Activity	Real GDP	Q	0.159	(0.150, 0.168)
	Real Compensation of Employees	Q	0.051	(0.037, 0.065)
	Employment	Q	0.028	(0.017, 0.041)
	Real Services Turnover	Q	0.119	(0.110, 0.130)
	Unemployment Rate	M	-0.052	(-0.063, -0.041)
	Inbound Tourism	M	0.020	(0.006, 0.034)
	Real Tourism Expenditure	M	0.064	(0.054, 0.074)
	Industrial Production	M	0.050	(0.040, 0.060)
	Real Tax Revenue	M	0.069	(0.061, 0.076)
	Retail Trade	M	0.088	(0.078, 0.098)
Expectations	ESI	M	0.106	(0.095, 0.112)
	EPU	M	-0.037	(-0.046, -0.028)
	Building Permits	M	0.050	(0.042, 0.059)
	Term Spread	W	-0.005	(-0.016, 0.006)
Financial Conditions	Household Credit Gap	Q	0.010	(0.003, 0.018)
	Firm Credit Gap	Q	-0.003	(-0.009, 0.004)
	Real Debt Securities MFCs	Q	0.001	(-0.012, 0.014)
	Real Debt Securities NFCs	Q	0.057	(0.044, 0.069)
	Real Quoted Shares MFCs	Q	0.043	(0.031, 0.054)
	Real Quoted Shares NFCs	Q	0.036	(0.022, 0.052)
	Malta 10-year Gov Bond Yield	M	-0.014	(-0.02, -0.007)
	Country Spread	M	-0.007	(-0.017, 0.003)
	MSE Index	W	0.011	(0.005, 0.017)
	EA Shadow Rate	W	0.000	(-0.002, 0.003)
International Trade	BDI	M	0.028	(0.016, 0.039)
	REER	M	-0.018	(-0.028, -0.009)
	Real Exports	M	0.009	(0.001, 0.018)
	Real Imports	M	0.041	(0.033, 0.050)

Source: Authors' calculations.

Notes: Posterior medians and 68% credible intervals are obtained from 3,000 retained draws.

B.5 Common factor variance share: posterior medians and credible intervals

Table B.2: Share of variance attributable to the common factor: posterior medians and 68% credible intervals.

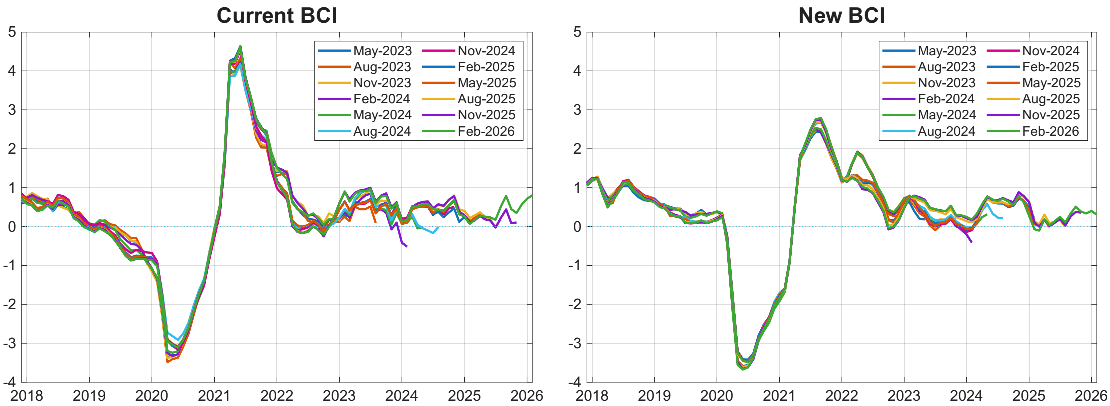
Category	Variable	Frequency	Variance share	
			Median	68% Interval
Real Activity	Real GDP	Q	0.920	(0.907, 0.932)
	Real Compensation of Employees	Q	0.083	(0.069, 0.097)
	Employment	Q	0.045	(0.038, 0.052)
	Real Services Turnover	Q	0.407	(0.344, 0.466)
	Unemployment Rate	M	0.084	(0.073, 0.095)
	Inbound Tourism	M	0.026	(0.023, 0.030)
	Real Tourism Expenditure	M	0.196	(0.171, 0.220)
	Industrial Production	M	0.075	(0.065, 0.087)
	Real Tax Revenue	M	0.011	(0.006, 0.027)
	Retail Trade	M	0.238	(0.212, 0.266)
Expectations	ESI	M	0.353	(0.315, 0.392)
	EPU	M	0.009	(0.007, 0.010)
	Building Permits	M	0.057	(0.046, 0.070)
	Term Spread	W	0.001	(0.001, 0.001)
Financial Conditions	Household Credit Gap	Q	0.022	(0.019, 0.026)
	Firm Credit Gap	Q	0.001	(0.001, 0.001)
	Real Debt Securities MFCs	Q	0.005	(0.004, 0.007)
	Real Debt Securities NFCs	Q	0.115	(0.093, 0.141)
	Real Quoted Shares MFCs	Q	0.011	(0.009, 0.014)
	Real Quoted Shares NFCs	Q	0.059	(0.046, 0.073)
	Malta 10-year Gov Bond Yield	M	0.018	(0.016, 0.020)
	Country Spread	M	0.036	(0.032, 0.041)
	MSE Index	W	0.002	(0.002, 0.003)
	EA Shadow Rate	W	0.000	(0.000, 0.000)
International Trade	BDI	M	0.021	(0.018, 0.024)
	REER	M	0.001	(0.001, 0.001)
	Real Exports	M	0.005	(0.000, 0.007)
	Real Imports	M	0.002	(0.000, 0.004)

Source: Authors' calculations.

Notes: Posterior medians and 68% credible intervals are obtained from 3,000 retained draws.

B.6 The New and Current BCIs across data vintages

Figure B.9: The New and Current Business Conditions Indices across the twelve vintages available as of the end of May 2023 till the end of February 2026 (respectively, right and left panel).



Source: Authors' calculations.

Notes: The x-axis represents time while the y-axis the value of the New and the Current BCIs.