# European Business Cycle Indicators

## 1st Quarter 2018

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1ˢᵗ Quarter 2018

## Special topic

- Nowcasting euro area GDP growth with Mixed Frequency Models

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## Recent developments in survey indicators

- Having peaked in December 2017 at levels last witnessed 17 years ago, the euro-area (EA) and EU Economic Sentiment Indicators (ESI) declined during the first quarter of 2018. Over the last three months, the indicators decreased by 2.7 (EA) and 2.6 (EU) points, remaining nevertheless at historically elevated levels of 112.6 (EA) and 112.5 (EU) points.

- The decline in the euro area was mainly due to a marked decrease in retail trade, but also small reductions in industry and services. Confidence remained broadly stable among consumers and improved in the construction sector. The results were similar at EU-level, with the difference that the decrease was particularly pronounced in industry, while the drop in retail trade was less severe than in the euro area.

- Among the seven largest EU economies, in 2018Q1, economic sentiment decreased markedly in the UK (-6.5), France (-4.4) and Germany (-3.4). The indicator decreased also in Italy (-2.0), and Spain (-1.0), while it increased in Poland (+3.3) and – more marginally – in the Netherlands (+0.8).

- Capacity utilisation in manufacturing increased for the seventh consecutive quarter (+0.7 percentage points in the euro area, +0.9 percentage points in the EU). Currently, capacity utilisation is at 84.5% (EA) / 83.9% (EU), i.e. clearly above the regions' respective long-term averages of around 81%. Also capacity utilisation in services saw an increase in the euro area (+0.6 points), while it remained broadly stable in the EU (+0.1). The current rates of 90.2% (EA) and 89.7% (EU) correspond to levels clearly above the respective long-term averages (calculated from 2011 onwards) of around 88.5%.

## Special topic: Nowcasting euro area GDP growth with Mixed Frequency Models

This special topic evaluates the nowcasting performance of the Mixed Frequency Data Sampling (MIDAS) regression model for euro area GDP growth in a pseudo real-time setting. The results of the MIDAS are compared with the performance of two benchmark models that exploit two distinct datasets of predictor variables and make use of different time-aggregation techniques. The results show that the MIDAS model, using the same information set (i.e. predictor variables), does not generally perform better than taking the simple average of the available higher-frequency predictor variables within quarters or the so-called 'blocking approach'. Yet, in times of turbulent economic conditions, when the timing information of the changes in the explanatory variables can play a greater role, some of the specifications appear to outperform the benchmark models.

# 1. RECENT DEVELOPMENTS IN SURVEY INDICATORS

## 1.1. EU and euro area

Having peaked in December 2017 at levels last witnessed 17 years ago, the euro-area (EA) and EU Economic Sentiment Indicators (ESI) declined during the first quarter of 2018 (see Graph 1.1.1). Over the last three months, the indicators decreased by 2.7 (EA) and 2.6 (EU) points, remaining nevertheless at historically elevated levels of 112.6 (EA) and 112.5 (EU) points.

**Graph 1.1.1: Economic Sentiment Indicator**
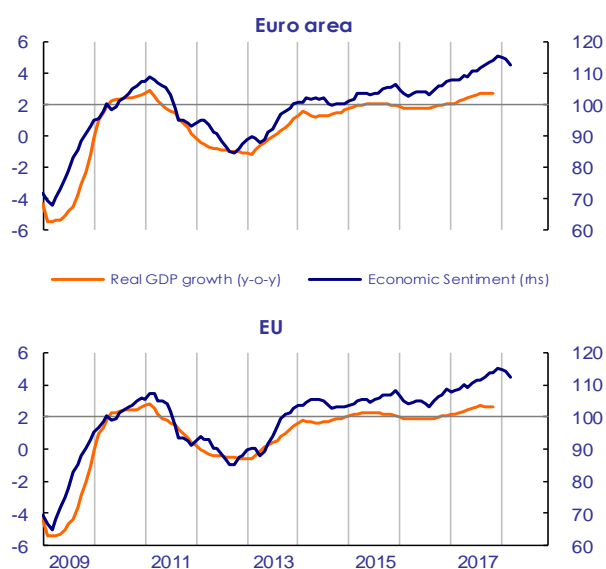


Note: The horizontal line (rhs) marks the long-term average of the survey indicators. Confidence indicators are expressed in balances of opinion and hard data in y-o-y changes. If necessary, monthly frequency is obtained by linear interpolation of quarterly data.

In line with the ESI results, Markit Economics' Composite PMI for the euro area lost momentum during 2018Q1. Similarly, after reaching a new all-time high in 2017Q4, the Ifo Business Climate Index (for Germany) declined in 2018Q1.

**Graph 1.1.2: Radar Charts**
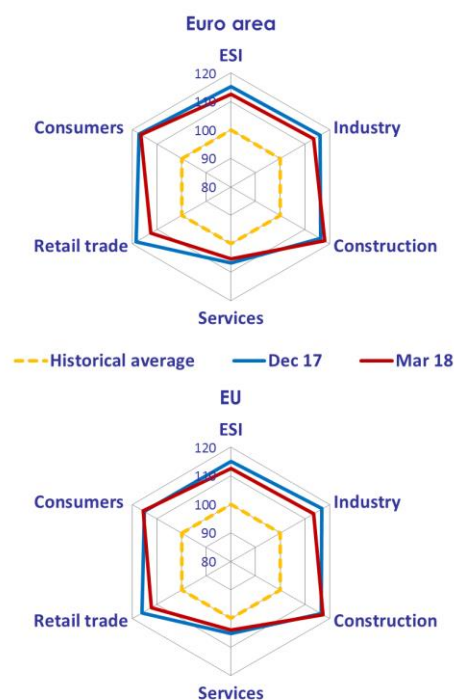


Note: A development away from the centre reflects an improvement of a given indicator. The ESI is computed with the following sector weights: industry 40%, services 30%, consumers 20%, construction 5%, retail trade 5%. Series are normalised to a mean of 100 and a standard deviation of 10. Historical averages are generally calculated from 1990q1. For more information on the radar charts see the Special Topic in the 2016q1 EBCI.

From a sectoral perspective, euro-area confidence improved only in the construction sector in 2018Q1, while it decreased markedly in the retail trade sector and, to a lesser degree, in industry and services. Confidence remained broadly stable among consumers (see Graph 1.1.2). The results were similar at EU-level. In the EU, the decrease was particularly pronounced in industry, while the drop in retail trade was less severe than in the euro area.

In terms of levels, all euro-area and EU confidence indicators remain well above their respective long-term averages. In particular, the confidence indicator for construction climbed to its highest level since December 2006.

Among the seven largest EU economies, in 2018Q1, economic sentiment decreased

markedly in Germany (-3.4), France (-4.4) and the UK (-6.5), the latter mostly driven by a drastic decrease in sentiment in manufacturing. The indicator decreased also in Italy (-2.0), and to some extent in Spain (-1.0), while it increased in Poland (+3.3) and – more marginally - in the Netherlands (+0.8).

## Sector developments

In both the euro area and the EU, **industrial confidence** worsened during 2018Q1, interrupting the upward trend that was prevailing since autumn last year. The indicators are now 2.4 (EA) and 3.1 (EU) points lower than in December 2017. As illustrated by Graph 1.1.3, industry confidence remains strong by historic standards in both the EA and the EU.

**Graph 1.1.3: Industry Confidence indicator**



**Euro area**

**EU**
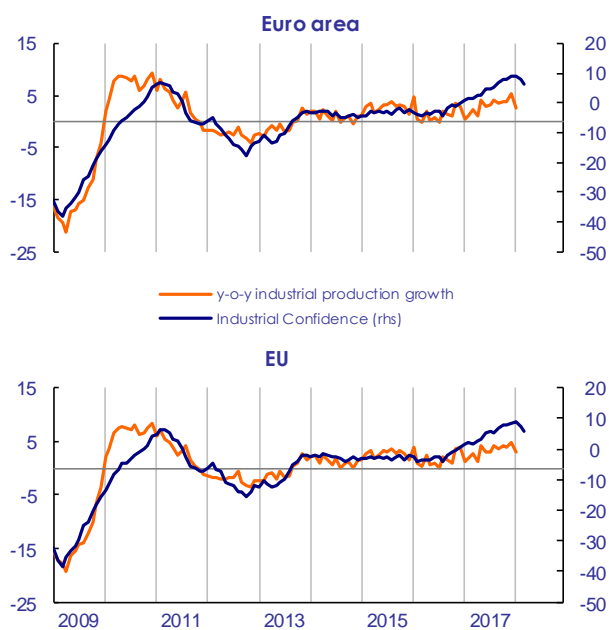
The fall in the confidence indicators was due to a marked decrease of managers' production expectations and a less severe worsening of their assessment of the stocks of finished products. Managers' evaluation of their order books worsened slightly in the EU, while it remained broadly stable in the euro area.

Of the components not included in the confidence indicators, managers' views on past production decreased strongly, while their assessment of export order books registered only a small decline in 2018Q1.

During the first quarter of 2018, selling price expectations lowered in both the euro-area and the EU. Also manufacturing managers' employment expectations declined, interrupting the upward trend that had started at the beginning of 2016 and led to record levels at the end of 2017 (see Graph 1.1.4).

**Graph 1.1.4: Employment - Industry Confidence indicator**



**Euro area**

**EU**
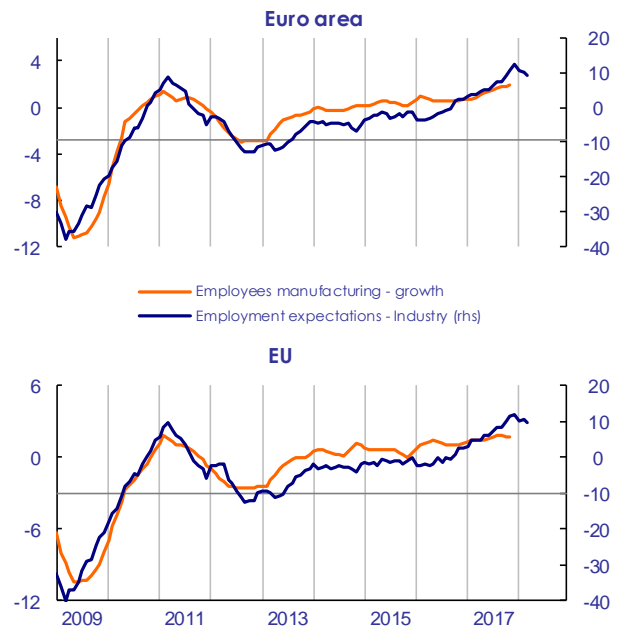
Focussing on the seven largest EU economies, a comparison of December 2017 and March 2018 readings shows a drastic decrease in the confidence indicator of the UK (-13.1), and a still marked decline in Germany (-3.3). The indicator declined also in Spain (-2.9), France (-2.3) and Italy (-1.5), while it remained broadly stable in the Netherlands (+0.3) and improved in Poland (+1.9).

The quarterly manufacturing survey (carried out in January) showed **capacity utilisation in manufacturing** to have increased for the seventh consecutive quarter (+0.7 percentage points in the euro area, +0.3 percentage points in the EU). Currently, capacity utilisation is at 84.5% (EA) and 83.9% (EU), i.e. clearly above the two regions' respective long-term averages of around 81%.

Also confidence in the **services sector** decreased in 2018Q1. The indicator lost 1.7 (EA) and 1.4 (EU) points over the quarter but remains comfortably above its long-term average (see Graph 1.1.5).

**Graph 1.1.5: Services Confidence indicator**

**Euro area**



Services value added growth — Service Confidence (rhs)

**EU**
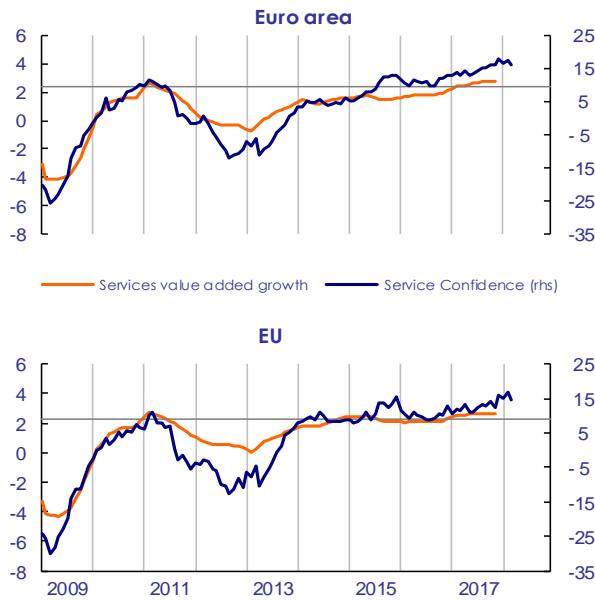


In the euro area, the worsening of the confidence indicator resulted from deteriorating views on past and expected demand, while managers' assessment of the past business situation was basically unchanged. In the EU, the decrease of the indicator came from managers' weaker assessment of past demand and the business situation, while managers' demand expectations remained broadly stable.

In both areas, service managers' employment expectations are at a higher level in March than in December, confirming the slow but steady upward trend observable since around mid-2016 (see Graph 1.1.6). Meanwhile, selling price expectations remained broadly unchanged in both areas.

Among the seven largest EU Member States, confidence in the services sector steamed ahead in Spain (+6.8), and Poland (+4.6), while gaining some momentum also in the Netherlands (+1.6). By contrast, the indicator decreased markedly in Germany (-4.5), France (-3.7) and Italy (-3.2), and remained essentially unchanged in the UK (-0.5).

**Capacity utilisation in services**, as measured by the quarterly survey in January, saw an increase of 0.6 points in the EA, while the indicator remained broadly stable in the EU (+0.1). The current rates of 90.2% (EA) and 89.7% (EU) correspond to levels clearly above

the long-term averages (calculated from 2011 onwards) of around 88½%.

**Graph 1.1.6: Employment - Services Confidence indicator**

**Euro area**



Employees services - growth
Employment expectations - Service (rhs)

**EU**
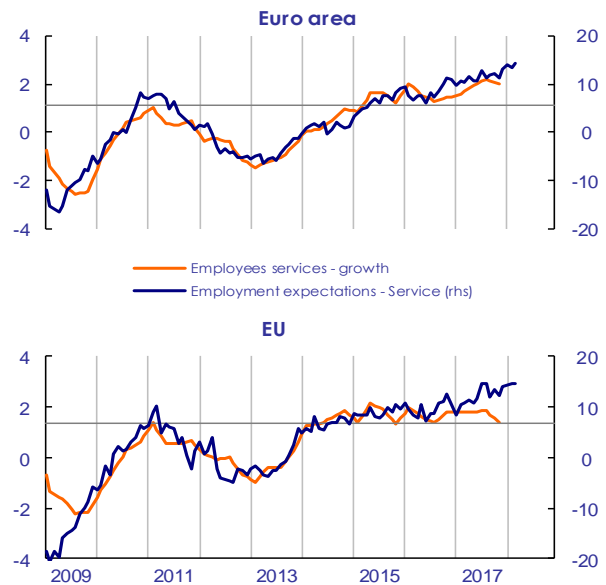


**Retail trade** confidence dropped in both the euro area (-4.4) and the EU (-2.6), offsetting earlier increases registered during 2017Q4. All in all, the two indicators are showing rather flat developments around historically high levels since late 2016/early 2017 (see Graph 1.1.7).

**Graph 1.1.7: Retail Trade Confidence indicator**

**Euro area**



Consumption growth — Retail Confidence (rhs)

**EU**
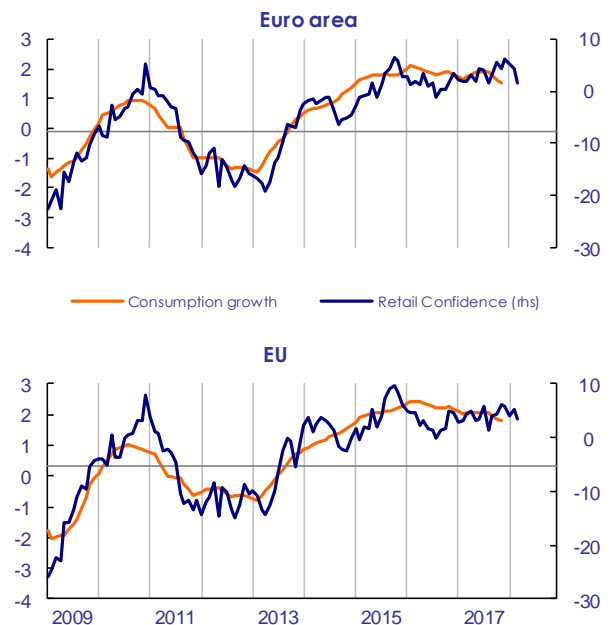


In the euro area, the decrease results from a strong deterioration of all three components (managers' appraisal of the past and future business situation and the volume of stocks),

while in the EU only managers' appraisal of the past business situation and the volume of stocks worsened while their assessment of the future business situation remained broadly stable.

At the level of the seven largest EU economies, confidence plummeted in Germany (-8.1), offsetting last quarter's substantial gains, and booked marked decreases in France (-5.2) and Italy (-5.1). Albeit to a lesser extent, the indicator decreased also in Poland (-2.4) and the Netherlands (-2.0). By contrast, the UK (+4.3) posted a marked increase, while sentiment in Spain (+0.3) remained broadly flat.

Continuing the upward trend that started in mid-2014, **construction** confidence increased further in 2018Q1, gaining 2.1 points on the quarter in the euro area; the increase was more minor in the EU (+0.9). In both areas, the appraisal of firms' current order books was brighter, while managers' employment expectations were more optimistic in the euro area, while they remained broadly unchanged in the EU.

Graph 1.1.8: Construction Confidence indicator
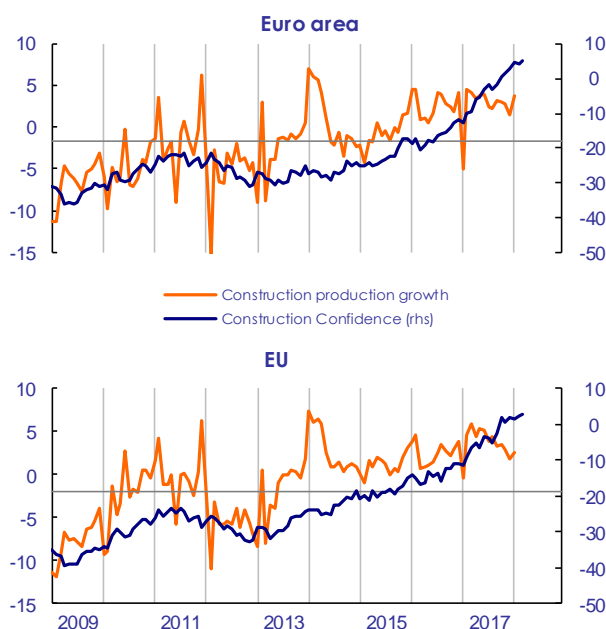


Among the seven largest EU economies, the indicator increased strikingly in Spain (+13.5, resulting from a dramatic rise in January followed by two smaller decreases in February and March). Confidence increased also in Germany (+2.2), Italy and Poland (both +1.8), while the indicator decreased markedly in the Netherlands (-5.8) and the UK (-4.1) and remained broadly stable in France (-0.3).

**Consumer confidence** remained broadly stable in 2018Q1. The indicators changed very little in March compared to December in both the euro area (-0.4) and the EU (+0.3). Both indicators remained at historically high levels (see Graph 1.1.9), last witnessed in spring 2001.

In both areas, consumers were more optimistic about unemployment developments over the next 12 months, while they were more pessimistic about the future the general economic situation of their country. Consumers' expectations about their personal financial situation remained virtually flat in both areas, while their savings expectations remained virtually unchanged in the EU and worsened in the EA.

Graph 1.1.9: Consumer Confidence indicator
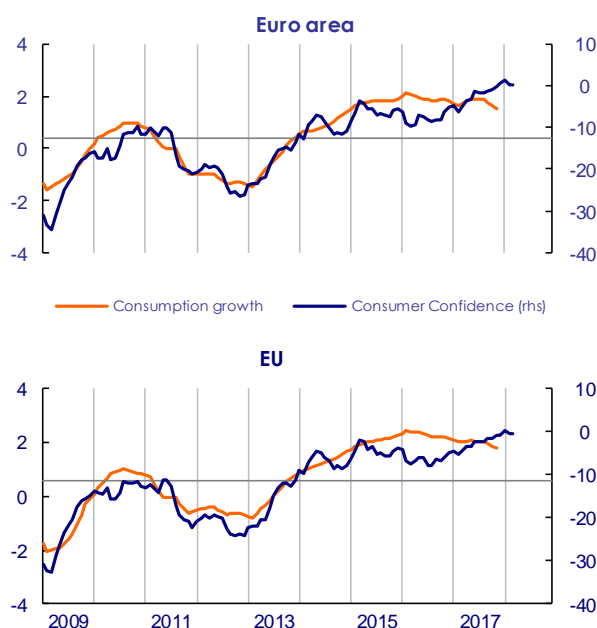


In the seven largest EU economies, consumer confidence improved markedly in the UK (+3.6) and booked somewhat more moderate improvements in the Netherlands (+1.1), while it deteriorated in France and Spain (both -2.0), and remained broadly unchanged in Germany (0.0), Italy (+0.8) and Poland (+0.9).

Confidence in the **financial services** sector (not included in the ESI) fell on the quarter (-2.4 in the euro area; -1.5 in the EU). However, considering the characteristic volatility of the

indicator, the 2018Q1 results can be interpreted as a continuation of the broad sideways movement already observed since the beginning of 2017 (see Graph 1.1.10).

In both regions, managers' assessment of the past business situation and past demand were appraised less positively, while managers were more optimistic concerning demand expectations.

**Graph 1.1.10: Financial Services Confidence indicator**
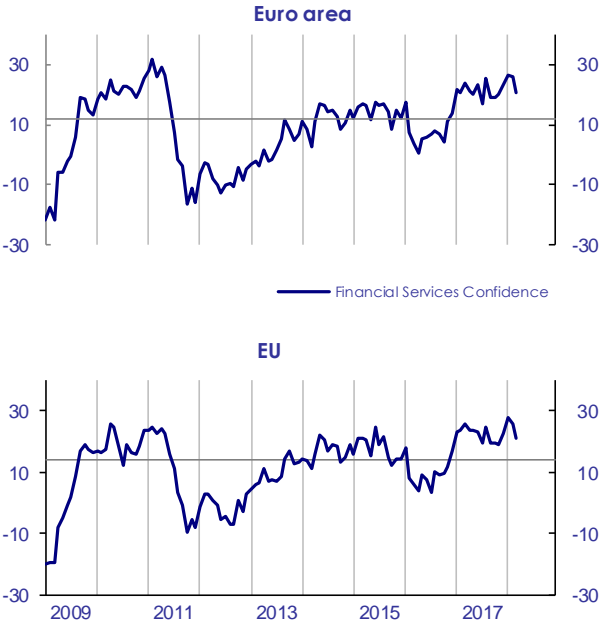


Reflecting the developments of overall sentiment, both the euro area and EU **climate tracers** (see Annex for details) remained in the expansion quadrant, while bending towards the downswing area (see Graphs 1.1.11 and 1.1.12).

**Graph 1.1.11: Euro area Climate Tracer**
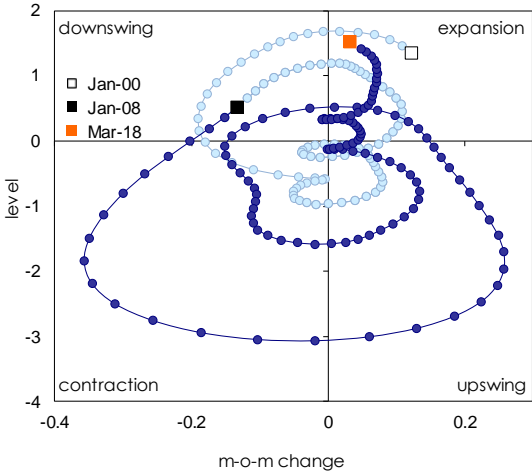


The sectoral climate tracers (see Graph 1.1.13) are in line with the overall tracers in so far as they are remaining in the expansion area but are pointing to the downswing quadrant. In the case of EU retail trade sector, the climate tracer is already entering the downswing area. Only the climate tracer for the services sector remained firmly in the expansion quadrant.

**Graph 1.1.12: EU Climate Tracer**
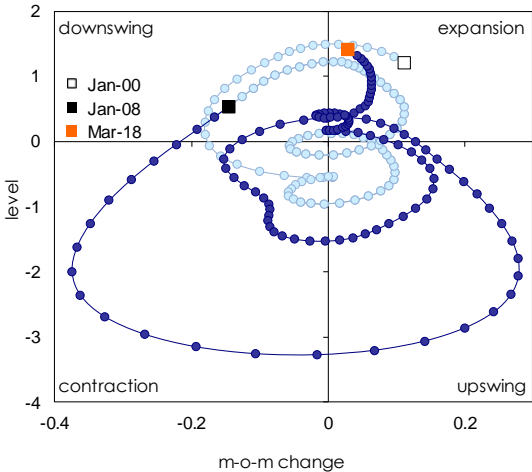
## Graph 1.1.13: Economic climate tracers across sectors

### Euro area

**Industry**



**Services**



**Retail trade**



**Construction**



**Consumers**



### EU

**Industry**



**Services**



**Retail trade**



**Construction**



**Consumers**
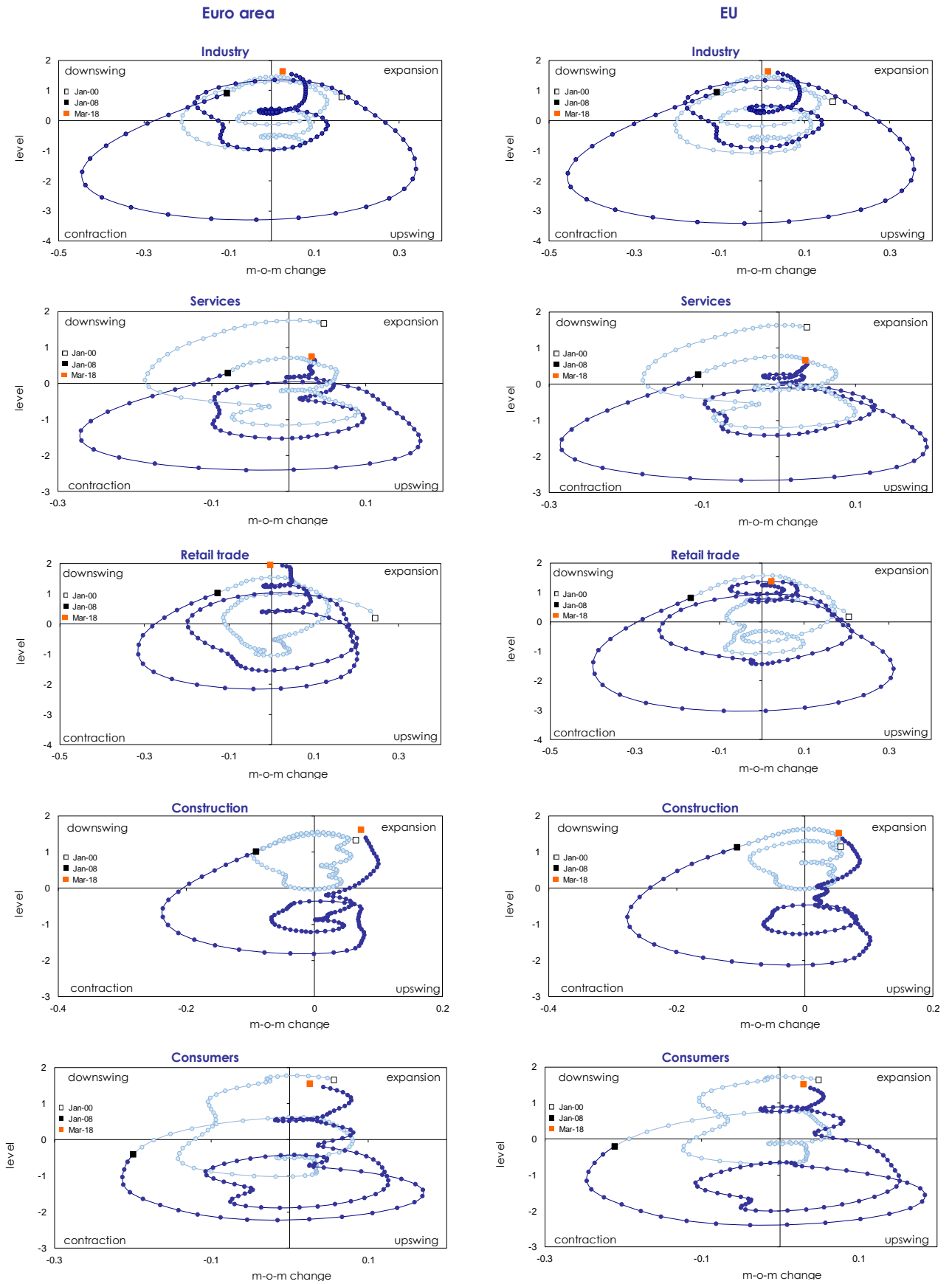
## 1.2. Selected Member States

Over the first quarter of 2018, economic sentiment worsened significantly in the UK (-6.5), France (-4.4) and Germany (-3.4). The indicator decreased also in Italy (-2.0) and, to some extent, in Spain (-1.0), while it increased slightly in the Netherlands (+0.8) and, more strongly so, in Poland (+3.3).

Sentiment in **Germany** interrupted the upward trend that was visible since mid-2016, losing 3.4 points compared to the end of 2017Q4. At 112.0 points, the indicator remained nonetheless very comfortably above its long-term average of 100. In terms of the climate tracer (see Graph 1.2.1), the German economy remains quite high in the expansion quadrant but its position is now bending towards the downswing area.

**Graph 1.2.1: Economic Sentiment Indicator and Climate Tracer for Germany**



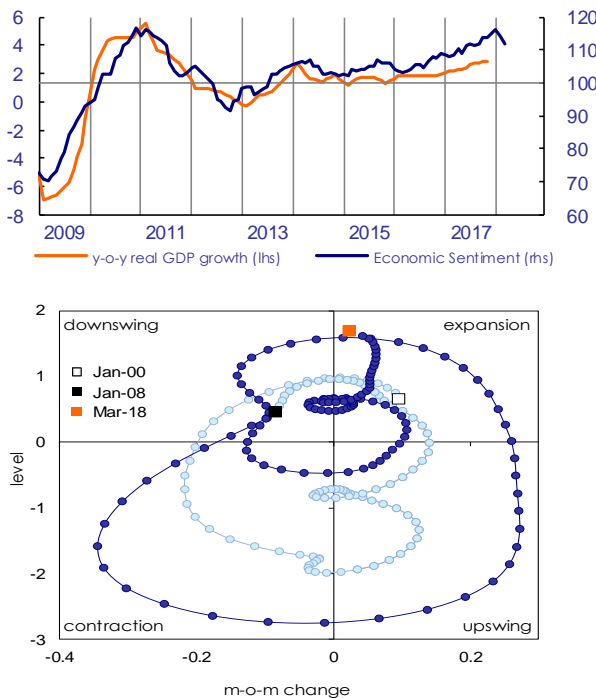From a sectoral perspective, only construction confidence was at a higher level in March 2018 than at the end of 2017Q4. Consumer confidence remained stable, while all the other business indicators are now at lower levels than at the end of 2017. In line with the ESI, and with the notable exception of the services sector, the sectoral confidence indicators were still at levels well in excess of their respective historical averages (see Graph 1.2.2). The level of confidence is particularly high in the German construction sector.

**Graph 1.2.2: Radar Chart for Germany**
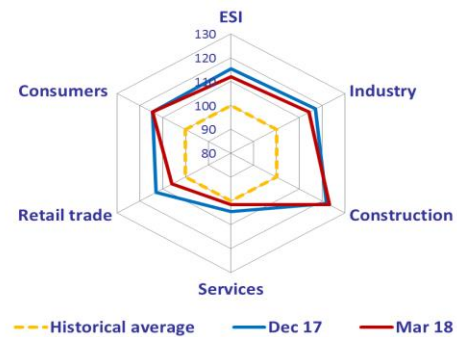


Also in **France** the upward trend observable since mid-2016 paused and the indicator lost 4.4 points over the quarter. At 109.5 points, the headline indicator remains however well above its long-term average of 100. The French climate tracer remains in the expansion area but is approaching the downswing quadrant (see Graph 1.2.3).

**Graph 1.2.3: Economic Sentiment Indicator and Climate Tracer for France**
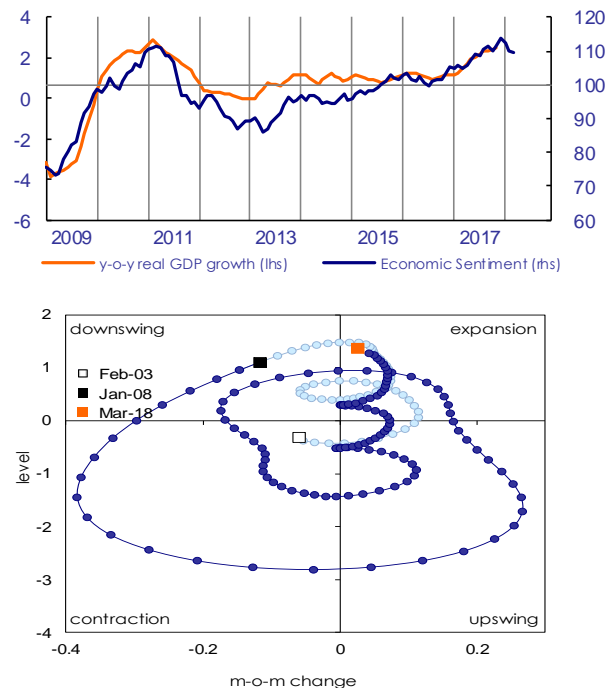


A look at the French radar chart (see Graph 1.2.4) reveals that all surveyed business sectors, except for the stable construction sector, signalled lower sentiment. The fall in

confidence was particularly strong in the retail trade and services sectors. In terms of levels, sentiment continued to exceed its long-term average in all surveyed parts of the economy.

**Graph 1.2.4: Radar Chart for France**



At sectoral level, it emerges that confidence worsened markedly in the services and retail trade sectors. Confidence decreased also in industry, while it improved in construction and remained virtually unchanged among consumers (see Graph 1.2.6). All sectoral indicators are clearly outperforming their respective historical averages.

**Graph 1.2.6: Radar Chart for Italy**



After some up and down, the **Italian** ESI ended the first quarter of 2018 at a lower level than in December (-2.0 points). From a longer-term perspective, in the last six months the Italian ESI showed only muted fluctuations around a rather high level of 109.8 points, clearly above its long-term average of 100. Also the Italian climate tracer (see Graph 1.2.5) stayed in the expansion quadrant, pointing however to the downswing area.

The **Spanish** ESI decreased slightly, finishing 2018Q1 1.0 point lower than in December 2017. At 109.0 points, the indicator continues being firmly above its long-term average of 100. Meanwhile, the country's climate tracer moved in the direction of the downswing quadrant, now standing just at the border between the downswing and expansion areas (see Graph 1.2.7).

**Graph 1.2.5: Economic Sentiment Indicator and Climate Tracer for Italy**

**Graph 1.2.7: Economic Sentiment Indicator and Climate Tracer for Spain**



y-o-y real GDP growth (lhs) — Economic Sentiment (rhs)



the Dutch climate tracer (see Graph 1.2.9) moved deeper into the expansion area.

**Graph 1.2.9: Economic Sentiment Indicator and Climate Tracer for the Netherlands**



y-o-y real GDP growth (lhs) — Economic Sentiment (rhs)
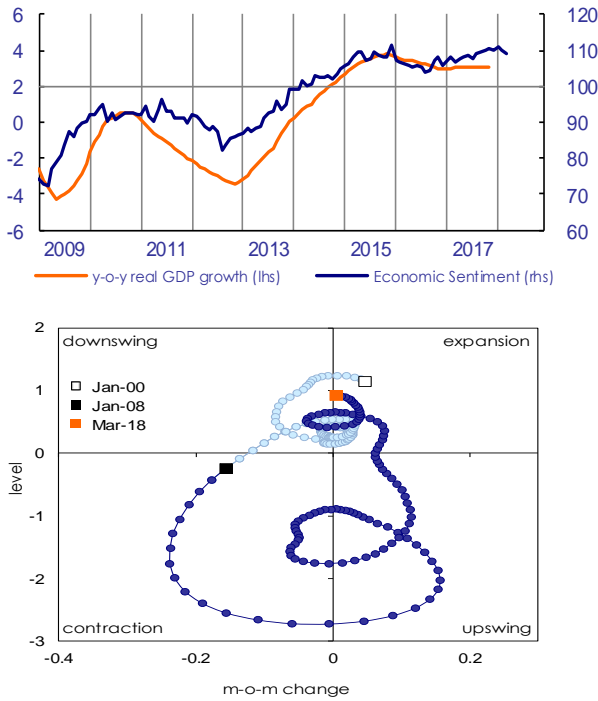


As the radar chart highlights (see Graph 1.2.8), confidence increased significantly in construction and, still markedly, in services. By contrast, confidence dropped in industry and among consumers, and remained broadly stable in the retail trade sector. Currently, despite the declines in industry and among consumers, confidence is scoring rather high by historic standards in all the sectors.

**Graph 1.2.8: Radar Chart for Spain**



- - - Historical average — Dec 17 — Mar 18
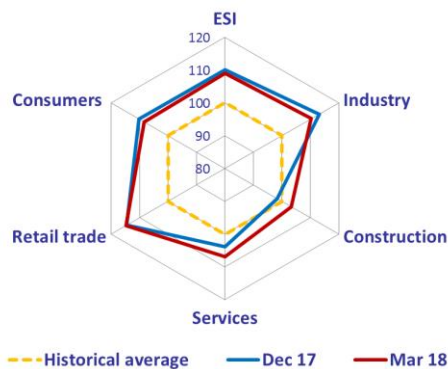
**Dutch** sentiment improved marginally during the first quarter of 2018. The Dutch ESI gained 0.8 points on the quarter and its current level of 112.8 points marks a new high in more than 10 years, well in excess of the indicators' long-term average of 100. In line with the positive results,

The Dutch radar chart (see Graph 1.2.10) shows that confidence edged up in services and among consumers, remained broadly stable in industry, while it worsened somewhat in retail trade and markedly in the construction sector (only partly offsetting the huge increase registered in the previous quarter). Confidence in industry, services, among consumers and, in particular, construction, is well above the respective historical averages. Only retail trade confidence is now at a level just below the historical benchmark.

**Graph 1.2.10: Radar Chart for the Netherlands**



- - - Historical average — Dec 17 — Mar 18
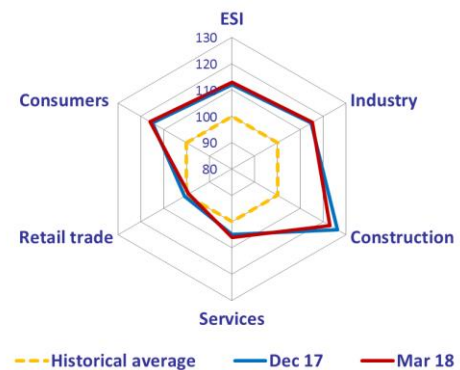
After nearly one year of broadly flat developments, sentiment in the **United Kingdom** worsened markedly during the first quarter of 2018 and is now 6.5 points lower than three months ago. Still, at 105.3 points, the indicator remained above its long-term average of 100. The UK climate tracer left the expansion area and entered the downswing quadrant (see Graph 1.2.11).

Despite a small decrease registered in March, **Polish** sentiment increased markedly in 2018Q1. The polish ESI was 3.3 points higher than at the end of 2017Q4, lifting the indicator's current reading (110.0 points) significantly above the long-term average. The Polish climate tracer moved further in the expansion quadrant (see Graph 1.2.13).

Graph 1.2.11: Economic Sentiment Indicator and Climate Tracer for the United Kingdom



Graph 1.2.13: Economic Sentiment Indicator and Climate Tracer for Poland



Focussing on sectoral developments, stronger confidence in retail trade and among consumers was more than offset by negative developments in the industrial and construction sectors. The fall in industry was particularly drastic. Confidence in the services sector remained broadly stable at its long term average (see Graph 1.2.12). Currently all other confidence indicators are above their respective long-term averages.

As the Polish radar chart (see Graph 1.2.14) shows, confidence improved strongly in services and, to a lesser extent, in industry and construction. Confidence remained broadly unchanged among consumers and worsened markedly in the retail trade sector. After the rise in services confidence, all the indicators are now well above their respective long-term averages.

Graph 1.2.12: Radar Chart for the UK



Graph 1.2.14: Radar Chart for Poland
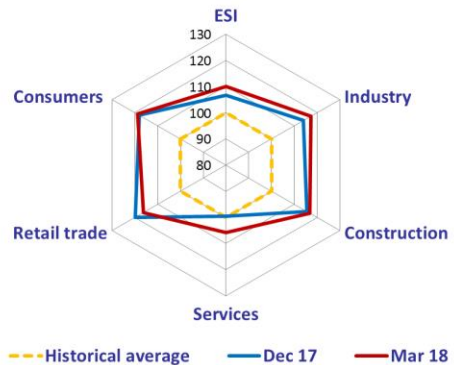
# 2. SPECIAL TOPIC: NOWCASTING EURO AREA GDP GROWTH WITH MIXED FREQUENCY MODELS

## Introduction

An early understanding of the underlying state of economic activity is important for decision makers in various sectors of the economy as they typically base their decisions on business cycle conditions. However, quarterly Gross Domestic Product (GDP), which is the most comprehensive and widely used variable to capture aggregate economic conditions, is released with a considerable time-lag that limits its usefulness in decision making. Furthermore, many other important macroeconomic indicators that are highly correlated with GDP growth are not necessarily sampled at the same frequency, but may be released more frequently. In order to overcome both the timeliness problem of GDP releases and the different frequencies of correlated variables, many models have been developed with diverse econometric methods and choice of predictor variables. In general, these aim at computing nowcasts of the GDP growth rate in search of superior forecasting accuracy and make use of information from indicators that are available at a monthly or higher frequency.

## The problem of time aggregation and the MIDAS approach

A majority of the standard econometric techniques applied in nowcasting and in bridge models implicitly assume that the explanatory variables are sampled at the frequency of the dependent variable and thus can be included in a regression model without frequency transformation. However, most of the economic variables which are highly correlated with GDP growth and have significant predictive power are of monthly frequency. This gives origin to the so-called mixed-frequency problem. In addition, in a pseudo real time setting (similarly to an actual nowcasting exercise), the ragged edge problem also arises due to the different publication lags of the indicators included in a data set upon which a nowcasting model is estimated. This essentially means that the

simple averaging of monthly variables, which are published with a significant delay (e.g., industrial production is published with a two month lag) is not possible due to the different timing of the last observations across the series. While econometric solutions to these problems (such as missing observations of the higher frequency series) range from simple intra- and extrapolation to more advanced Kalman filtering and beyond, the discussion will be limited to the ones used in this special topic.

The simplest and most frequently used method to convert higher-frequency data to the frequency of the reference variable is simple averaging over time, i.e. calculating the arithmetic average of the predictor variables' values published between two releases of the lower frequency variable. However, this technique may be applied only when the problem of ragged edge is not present (i.e. all the explanatory variables are published at the same time). One important feature when taking the arithmetic average in between two observations of the lower frequency series is the underlying assumption that higher frequency observations influence the outcome of the lower-frequency variable with the same weight, hence disregarding the additional information that the timing of changes to the high frequency explanatory variables may carry.[1] This assumption can be seen as restrictive in certain circumstances as the forecaster may want to attach a greater weight to the values of the predictor variable that are published closer to the release of the lower-frequency variable. In other words, one might believe that recently published data is more indicative to the outcome of the nowcasted variable than data published several

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[1] For example, a shock to e.g. industrial production may have different (less pronounced) effects on GDP growth in the reference quarter and the next one if it happens in the first month of a given quarter than in the third one.

periods before. A potential remedy could be the estimation of each of the weight coefficients of the lags of the high frequency variables in a linear regression model.[2]

Even though estimating the weight coefficients is a straightforward solution, the number of parameters to be estimated proliferates quickly, as the gap between the frequency of the dependent variable and explanatory variable widens. When using relatively short time series for the lower frequency series or very high frequency data as explanatory variable, the large number of estimated parameters leads to a significant loss of degrees of freedom, and thus potentially inefficient estimates.

An alternative strategy to overcome both the issue of mixed frequency and ragged edge is the blocking approach of Carriero et al. (2012). Originally applied to signal processing in engineering, it relatively quickly adapted to econometric modelling because of its suitability to handle the abovementioned problems. The technique is fairly simple and requires only data manipulation, as it attempts to distribute the high frequency indicator into a number of low frequency variables. For example, in a setting where the high frequency variable is monthly, whereas the nowcasted one is quarterly, the blocking approach creates three quarterly series from the monthly indicator. The first newly created low frequency variable includes the monthly variables' observations from the first month of each quarter; the second one corresponds to the second months, while the third series collects observations from the third month of the quarters. Although its relative simplicity is appealing, the drawback of the blocking approach is exactly the way it creates the low frequency series; the method results in a proliferation of series, entailing the need for restricting the number of variables included in standard regression models.[3]

The Mixed Frequency Data Sampling (MIDAS) approach[4] was first introduced by Ghysels et al. (2004) to address parameter proliferation, while preserving potential advantages emerging from explicitly modeling the timing of higher frequency variables, by fitting a polynomial function to the (weight) coefficients of the lags of explanatory variables. This method models the weight parameters of the lags of the higher frequency series, which directly affect the time-aggregation process and hence the way the lags of the explanatory variables impact on the dependent variable. Furthermore, the fitted function can have any kind of functional form, and a number of them have been proposed in the literature. Some of the most common weighting functions on the lag structure are the step-weighting, (exponential) Almon and Beta functions. However, there is a clear trade-off between the flexibility of the functional form and the number of parameters to be estimated. For example, to fit a quadratic function on the lags of the explanatory variable, only two parameters need to be estimated, whereas a higher degree polynomial or a highly nonlinear specification require the estimation of an increasing number of parameters. A parsimonious specification on the other hand (which should be the preferred model), allows for the inclusion of many lags of the explanatory variables, with possibly a slowly decaying weighting profile, and only two or three estimated parameters corresponding to the fitted function.

Most of the literature on MIDAS models concentrates on forecasting quarterly GDP growth series using monthly, weekly or daily financial series. The latter, in particular stock market data, interest rate quotes or volatility indexes, offer the opportunity to produce updated nowcasts each day within a quarter, accounting for the latest available information on economic conditions. An example for the

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[2] Note that these coefficients determine the weights with which the lags of the higher frequency series influence the evolution of the lower frequency dependent variable.

[3] For further discussion on the blocking approach in a nowcasting exercise, see Gayer et al. (2014).

[4] In essence, MIDAS allows for the regression of variables sampled at different frequencies. Therefore, the predictor variables may be included without the need of transformation of the higher frequency indicator (e.g. monthly indicators such as industrial production) to the frequency of the reference variable (e.g. quarterly GDP growth).

inclusion of daily or intra-daily data in the forecasting of quarterly GDP growth is presented in Tay (2006), who used daily stock returns in an autoregressive distributed lag (ARDL), a MIDAS and a benchmark model. He concluded that MIDAS outperforms the benchmark model with financial data, but not necessarily the ARDL one.

Some other studies focus on the efficient use of available monthly data across different modelling techniques. Clements and Galvão (2008) looked at whether their MIDAS specification, which included an autoregressive term of the dependent variable, can improve real-time forecasts of US output growth. They found that their model outperformed simple ARDL models at a short horizon and thus concluded that MIDAS effectively exploits the information in monthly data. Armesto, Engemann and Owyang (2010) in their study explore different ways of handling mixed frequency data, such as simple time averaging, a step-weighting function or MIDAS. Their results reveal that averaging the higher-frequency data to match the frequency of the lower one does not result in worse forecasting power than the one of MIDAS especially when end-of-period results are compared. However, they add that in case of intra-period[5] predictions (and certain forecasted variables), the MIDAS methodology can be a competitive alternative to other frequency conversion techniques as it produces more accurate forecast by modelling the flow of data within the low frequency period.[6]

## Empirical models for comparison

In this special topic, we examine the nowcasting performance of three different models: a simple linear model with only two explanatory variables, a larger static factor-based model which builds on real, survey and financial data and MIDAS models that are compared pairwise to the previous two models using the same information sets. The objective is to explore whether the additional information on the timing of the fresh observations of the higher frequency series, as captured by MIDAS, represents a considerable improvement in nowcasting performance over the existing models and methods of time-aggregation.

The analysis is based on a pseudo real-time exercise, with the out-of-sample accuracy of the models assessed at the end of each month of a given quarter through the calculation of Root Mean Squared Errors (RMSE) and hit ratios.[7] This ensures that we do not resort only to end-of-period nowcasting results, but evaluate the intra-period performance as well. Furthermore, in our attempt to closely imitate a real-time nowcasting exercise we replicate data-availability constraints[8], and the model is continuously re-estimated using an updated dataset before each nowcast.

The first benchmark model is a simple linear model estimated with Ordinary Least Squares (OLS), regressing quarterly euro area GDP growth on the level of survey confidence indicators together with their lags as additional predictor variables.[9] The frequency transformation in this model is performed by simple averaging within quarters. Note that in the first month of a new quarter this method takes the published value of the survey as a proxy for the whole quarter, while in the second month it computes the average of the first and second month's value. Whenever all the three monthly values are available, the arithmetic average of all monthly indicators for that quarter is used. Regarding the choice of survey indicators, the contemporaneous euro area

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[5] Intra-period predictions refer to the situation when new observations of the high frequency series are already available from the reference period of the low frequency variable.

[6] There is also a large literature on more sophisticated MIDAS models, like the MIDAS-VAR of Ghysels (2016) or the Markov-Switching MIDAS of Foroni, Guérin and Marcellino (2015), which are not covered in this special feature.

[7] Hit ratios are the proportions with which the model correctly predicts the direction of change in the dependent variable. In our case, this corresponds to an acceleration or deceleration of quarterly GDP growth.

[8] For example, monthly variables with a significant release lag enter the estimation sample only later than timely indicators.

[9] These survey data are readily available already at the end of the reference month, thus providing an early indication of economic conditions.

industrial confidence indicator, its lagged value (i.e. the previous quarter's average) and the one quarter lagged euro area services confidence indicator enter the equation. The selection of the indicators was based on in-sample fit of the models, whereby backward stepwise selection was applied to minimize the residual sum of square (RSS).[10] Since it is a 'general to specific' modelling approach, this involves the elimination of explanatory variables that do not improve the model fit.

The second benchmark model is a static factor model that involves the implementation of the blocking approach to handle the mixed-frequency problem. The dataset used in this model consists of 29 variables of which 26 are of monthly frequency, while the remaining three are quarterly series. Most of the monthly variables are survey indicators (e.g. answers to specific questions in the context of the European Commission's Business and Consumer Surveys[11]), but both real economic variables (e.g. euro area industrial production indices) and financial data[12] series are also included. After applying appropriate transformations to each time series, a four-step procedure is conducted to obtain a nowcast for the reference quarter.[13]

Since the focus here is on the assessment of the frequency conversion approach of MIDAS versus the other two methods discussed above, the estimated MIDAS models use exactly the same information sets as the benchmark models. However, instead of applying the quarterly averaging or the blocking approach, we include the indicators in the model without frequency

conversion, in line with the MIDAS approach.[14] Therefore, the potential gain of MIDAS models in nowcasting performance should mainly come from the additional information on the timing of the monthly observations that MIDAS accounts for.

## Results

### Comparison with the linear model and time averaging

In what follows, the out-of-sample nowcasting performance of the MIDAS model is compared to the benchmark models over four different periods. Given the volatility and irregularity of GDP growth during the turbulent times of the financial crisis and the sovereign debt crisis, it is necessary to evaluate the model performance in sub periods and not only over a longer time horizon. These periods, for which RMSE statistics and hit ratios are computed, correspond to the Great Recession (2008q1-2009q4), the Great Recession and the euro area sovereign debt crisis (2008q1-2012q4) and the subsequent recovery and expansion that started in 2013 (2013q1-2017q4). Lastly, the results over a longer horizon are presented as well, starting with the financial crisis and ending at the end of our sample (2008q1-2017q4).

Table 1 shows the results of the intra-period and end-of-period evaluation statistics over the four horizons.[15] The table is organized as follows: the first column presents the RMSE of the linear model; the second (Midas-const) uses a MIDAS specification which is constrained to use exactly the same set of monthly indicators and lag structure as the linear model;[16] the third

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[10] A similar method, the so-called best subset selection, which searches through all the possible combination of predictors led to the same, relatively parsimonious model as the backward stepwise selection.

[11] For further details see the User Guide of the Joint Harmonised EU Programme of Business and Consumer surveys.

[12] US stock indices or commodity price index, among others.

[13] Due to space limitations, we refrain from detailing these four steps here; a description of the modelling approach, a detailed explanation of the blocking approach and the transformation of monthly variables, as well as the estimation and calculation of nowcast with the static factor model can be found in Gayer et al (2014).

[14] Note that trending series (e.g. industrial production, stock and commodity prices, etc.) are still transformed in order to remove unit roots.

[15] Intra-period results correspond to the rows labeled by month 1 and month 2, while the end-of-period ones are presented in the rows of months 3.

[16] For all of the MIDAS specification, Almon lag weighting was used to place restrictions on lag coefficients of the explanatory variable. This technique models the regression coefficients as a quadratic or higher degree lag polynomial. Although we experimented with other weighting methods (e.g. step weighting), the results did not differ considerably and

(MIDAS-opt) reports the results of a MIDAS in which the lag length of the monthly explanatory variables (i.e. industrial confidence and services confidence indices) is selected by picking the model that produces the minimum out-of-sample RMSE from among models with different lag lengths.[17] Thus, this model departs from the somewhat restrictive assumptions of the previous MIDAS model and is allowed to fit a polynomial function on more lag coefficients.[18]

**Table 1: Model results (small dataset)**

| | RMSE | | | Hit Ratio | | |
|---|---|---|---|---|---|---|
| | Linear | MIDAS-const. | MIDAS-opt. | Linear | MIDAS-const. | MIDAS-opt. |
| | 2008q1 - 2009q4 | | | | | |
| Month 1 | 0.63 | 0.55 | 0.39 | 25.0% | 50.0% | 50.0% |
| Month 2 | 0.52 | 0.45 | 0.30 | 62.5% | 62.5% | 62.5% |
| Month 3 | 0.43 | 0.43 | 0.49 | 62.5% | 62.5% | 62.5% |
| | 2008q1 - 2012q4 | | | | | |
| Month 1 | 0.46 | 0.41 | 0.36 | 65.0% | 65.0% | 60.0% |
| Month 2 | 0.39 | 0.37 | 0.27 | 75.0% | 70.0% | 70.0% |
| Month 3 | 0.35 | 0.37 | 0.39 | 70.0% | 70.0% | 70.0% |
| | 2013q1 - 2017q4 | | | | | |
| Month 1 | 0.25 | 0.27 | 0.26 | 57.9% | 57.9% | 68.4% |
| Month 2 | 0.25 | 0.31 | 0.26 | 63.2% | 57.9% | 63.2% |
| Month 3 | 0.24 | 0.25 | 0.23 | 57.9% | 68.4% | 63.2% |
| | 2008q1 - 2017q4 | | | | | |
| Month 1 | 0.51 | 0.48 | 0.43 | 61.5% | 61.5% | 64.1% |
| Month 2 | 0.45 | 0.47 | 0.38 | 69.2% | 64.1% | 66.7% |
| Month 3 | 0.42 | 0.44 | 0.44 | 64.1% | 69.2% | 66.7% |

Source: own calculations

Confirming the prior statement on the volatility of quarterly GDP growth during the global financial crisis, the RMSEs of the linear and constrained MIDAS models are around twice as large as the same statistics over the post-2013 period. Interestingly, in the crisis period, the MIDAS-const model provides slightly more accurate or equivalent nowcasts than the linear

model in terms of RMSE. The advantage of MIDAS is however more evident when looking at intra-period nowcasts, while the end-of-period results are broadly the same. Regarding the hit ratios during the crisis, the MIDAS-specification performs similarly to the benchmark model, at least once the predictor values for the second and third month are available.

A similar pattern between the RMSE of the benchmark and the MIDAS-const model can be noted over the 2008q1-2012q4 ('extended crisis') horizon, with the linear model providing slightly better forecasts when all the three monthly values are available within the reference quarter. In the period of relatively low volatility, which started around early 2013 following the sovereign debt crisis, the linear model slightly outperforms the MIDAS-const model both intra- and end-of-period. This is also the case when covering the entire evaluation horizon (for Month 2 and 3).

Regarding the MIDAS-opt model, which uses an optimal out-of-sample lag length selection, the results are broadly in line with our expectations: this specification produces the lowest RMSE in the first and second months of the more volatile subperiods, but its performance worsens both in absolute terms and compared to the other models end-of-period. In the more tranquil period (2013q1-2017q4) the specification's performance is very similar to the one of the linear model.

## Comparison with the factor model and the blocking approach

In this section, we compare the performance of the MIDAS approach to that of the static factor model, again focusing on different sub-periods. In order to minimize the differences between the two models, we adapt the dataset in the following way: instead of applying the blocking approach (i.e. distributing the monthly observations into three quarterly variables and including the most recent one in the principal component analysis), we extract four factors from the monthly variables. These monthly factors then enter the MIDAS model along with the untransformed quarterly variables.

Table 2 below presents the RMSE statistics and hit ratios for the factor model and a MIDAS specification, in which four factors are included.

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therefore only the specification with Almon weighting and a quadratic polynomial is presented.

[17] Because of the applied selection, which chooses an optimal model based on out-of-sample statistics, this specification is geared towards out-of-sample nowcasting performance. However, due to the longer lag length, this model is not directly comparable to the other two.

[18] The model with the minimum RMSE was the one in which six lags of the explanatory variables were included. Therefore, Table 1 presents the nowcast evaluation statistics for this specification. Note, that this does not lead to an increase in the number of parameters to be estimated, as only a second degree polynomial is fit regardless of the number of lags included. Furthermore, the inclusion of many lagged series does not necessarily mean that the model has a strong autoregressive nature; if the fitted polynomial function attaches low weights to the lagged series that are not recent, the last few observations still dominate the time-aggregation.

As an early conclusion, the MIDAS specification does not perform better in any of the sub-periods. As a matter of fact, the MIDAS approach yields an RMSE that is on average approximately 30% higher than that of the factor model in the third month of the reference quarter. It is interesting to note though, that the RMSE of the nowcasts of the MIDAS model in the second months are lower than those in the third months, i.e. the simple MIDAS-factor model run in the second month provides more accurate forecasts than the model run in the third month. Regarding the hit ratios, however, the two models are comparative in terms of indicating de- or acceleration of GDP growth in both in the second and third months. In sum, the MIDAS-factor approach, which tries to harness the additional information in the high frequency principal components, does not seem to perform better than a static factor model with the blocking approach.

**Table 2: Model results (large dataset)**

|  | RMSE | | Hit Ratio | |
|---|---|---|---|---|
|  | Factor | MIDAS-factor | Factor | MIDAS-factor |
| | 2008q1 - 2009q4 | | | |
| Month 1 | 1.11 | 1.14 | 71.4% | 85.7% |
| Month 2 | 1.01 | 1.05 | 85.7% | 85.7% |
| Month 3 | 0.94 | 1.15 | 87.5% | 85.7% |
| | 2008q1 - 2012q4 | | | |
| Month 1 | 0.74 | 0.78 | 68.4% | 78.9% |
| Month 2 | 0.67 | 0.72 | 73.7% | 78.9% |
| Month 3 | 0.63 | 0.80 | 68.4% | 68.4% |
| | 2013q1 - 2017q4 | | | |
| Month 1 | 0.23 | 0.28 | 57.9% | 63.2% |
| Month 2 | 0.22 | 0.25 | 42.1% | 52.6% |
| Month 3 | 0.21 | 0.28 | 52.6% | 57.9% |
| | 2008q1 - 2017q4 | | | |
| Month 1 | 0.56 | 0.59 | 63.2% | 71.1% |
| Month 2 | 0.50 | 0.55 | 65.8% | 57.9% |
| Month 3 | 0.47 | 0.61 | 60.5% | 63.2% |

Source: own calculations

## Conclusions

One of the most important tasks of applied economic forecasting is to correctly inform decision-makers about the state of the economy. To this end, vast amount of econometric techniques have been proposed, offering solutions to the most problematic issues of nowcasting or short term forecasting. One of those relates to mixed data frequencies, to exploit early signals of available indicators to predict the outcome of a lower frequency variable.

This special topic evaluated the nowcasting performance of the MIDAS approach compared to two alternative techniques used by DG ECFIN for dealing with mixed frequency data. Our findings confirm the conclusions of other studies, that there is no marked or systematic gain in accuracy of MIDAS nowcasts over the existing methods. Nevertheless, some of the specifications over certain horizons (e.g. in turbulent economic conditions, when the timing information of the changes in the explanatory variables can play a greater role) may outperform the benchmark models.

All in all, it should be highlighted that the merits of the MIDAS approach are best exploited when the number of low frequency predictor variables or the included lags of them are relatively large or the frequencies of the regressors and the regressed variable differ substantially. Both of these cases result in parameter proliferation, to which the MIDAS approach provides an elegant and parsimonious solution by directly modelling the lag coefficients. Finally, the performance of any (nowcasting) model is known to be data-dependent. To put it differently, what works for one series (here: euro area GDP growth) may not necessarily do so for another.

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# ANNEX

## Reference series

| Confidence indicators | Reference series from Eurostat, via Ecowin (volume/year-on-year growth rates) |
|---|---|
| Total economy (ESI) | GDP, seasonally- and calendar-adjusted |
| Industry | Industrial production, working day-adjusted |
| Services | Gross value added for the private services sector, seasonally- and calendar-adjusted |
| Consumption | Household and NPISH final consumption expenditure, seasonally- and calendar-adjusted |
| Retail | Household and NPISH final consumption expenditure, seasonally- and calendar-adjusted |
| Building | Production index for building and civil engineering, trend-cycle component |

## Economic Sentiment Indicator

The economic sentiment indicator (ESI) is a weighted average of the balances of replies to selected questions addressed to firms and consumers in five sectors covered by the EU Business and Consumer Surveys Programme. The sectors covered are industry (weight 40 %), services (30 %), consumers (20 %), retail (5 %) and construction (5 %).

Balances are constructed as the difference between the percentages of respondents giving positive and negative replies. EU and euro-area aggregates are calculated on the basis of the national results and seasonally adjusted. The ESI is scaled to a long-term mean of 100 and a standard deviation of 10. Thus, values above 100 indicate above-average economic sentiment and vice versa. Further details on the construction of the ESI can be found here.

Long time series (ESI and confidence indices) are available here.

## Economic Climate Tracer

The economic climate tracer is a two-stage procedure. The first stage consists of building economic climate indicators, based on principal component analyses of balance series (s.a.) from five surveys. The input series are as follows: industry: five of the monthly survey questions (employment and selling-price expectations are excluded); services: all five monthly questions; consumers: nine questions (price-related questions and the question about the current financial situation are excluded); retail: all five monthly questions; building: all four monthly questions. The economic climate indicator (ECI) is a weighted average of the five sector climate indicators. The sector weights are equal to those underlying the Economic Sentiment Indicator (ESI, see above).

In the second stage, all climate indicators are smoothed using the HP filter in order to eliminate short-term fluctuations of a period of less than 18 months. The smoothed series are then normalised (zero mean and unit standard deviation). The resulting series are plotted against their first differences. The four quadrants of the graph, corresponding to the four business cycle phases, are crossed in an anti-clockwise movement and can be described as: above average and increasing (top right, 'expansion'), above average but decreasing (top left, 'downswing'), below average and decreasing (bottom left, 'contraction') and below average but increasing (bottom right, 'upswing'). Cyclical peaks are positioned in the top centre of the graph and troughs in the bottom centre. In order to make the graphs more readable, two colours have been used for the tracer. The darker line shows developments in the current cycle, which in the EU and euro area roughly started in January 2008.

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