Forecasting the European GDP using the (MI)xed (DA)ta (S)ampling models: The key role of the Consumption Sentiment Leading Indicator

Working paper

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Abstract

The consequences of the recent financial and health crises have significantly queried global confidence, giving a boost to the interest and need of signifying the short-run economic activity prospects and business cycle patterns internationally using leading indicators. As such, our analysis aims to evaluate the predictive power of quarterly GDP growth in the European Union through the MIDAS modelling approach using the so-called 'soft' survey and financial leading indicators sampled at a higher monthly frequency. Our results suggest that it may be favorable to include soft predictors sampled at a higher frequency than GDP growth according to *bias* and *efficiency principles*. Remarkably, the unequivocal role of the Consumer Survey Confidence Indicator in describing and anticipating movements in the EU GDP growth and other European countries through the MIDAS models is depicted.

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1. Introduction

Forecasting key macroeconomic variables is of paramount importance to both local governments and policymakers in major economic organizations and institutions including the European Commission (EC), the European Central Bank (ECB), and the International Monetary Fund (IMF), among others. During the last two decades, financial and health crises – the financial crisis of 2007-2008 and the most recent COVID-19 devastating health and economic crisis along with the Russian invasion of Ukraine severely littered the worldwide economy. The consequences of those crises along with climate and nature crises, rising energy costs, and rising inflation, which are at the forefront lately, have significantly queried global confidence, giving a boost to the interest and need of signifying the short-run economic activity prospects and business cycle patterns internationally. Endeavoring to accomplish those objectives, Composite Economic Indices – Lagging, Coincident, and Leading – have been developed worldwide. Examples of such Indicators are the Conference Board (CB) Lagging, Coincident, and Leading Economic Indices for the US, the Euro Area, as well as other major European economies like Germany and France, the Organization of Economic Cooperation and Development (OECD) Leading Indicators for the OECD and non-OECD countries, as well as the Cyprus Composite Leading Economic Index (CCLEI).

Among the most well-known Coincident Indicators are the Aruoba, Diebold, and Scotti (ADS) real-time measurement (2009) and the Weekly Economic Index (WEI) proposed by Lewis, Mertens, Stock, and Trivedi (2022) for the US, in which the significant role of the high-frequency data is recognized. Both are real-time measurements of economic activity, providing a quantitative measure of the current state and wealth of the economy based on mixed- and high-frequency data. The use of high-frequency data – timely available data is extremely important in tracking and monitoring the state of the economy, especially during turbulent periods where unexpected events occur such as that of the COVID-19 crisis. Nevertheless, in the case of dealing with mixed-frequency data, classical models consider the same low frequency of all series by simply aggregating their higher frequency into a common low frequency. For instance, it could be the case where a policymaker is interested in tracking the current state of the economy, e.g. GDP, based on the higher frequency information coming from the labor and investment sectors. While GDP is only available at a quarterly frequency, employment measures and stock prices are available at higher monthly and weekly frequencies, respectively. In that case, the conventional model would simply aggregate the higher frequency data by taking either their average or sum within each quarter. Although it might be an attractive approach amid its simplicity, pooling higher frequency data causes information loss and creates dynamics in the low-frequency model that differ from those within the high/mixed-frequency model (Ghysels and Marcellino, 2018).

Solutions to the conventional temporal aggregation approach arise when studying regression models that exploit the mixed sampling frequencies of the data. Our study employs the MI(xed) Da(ta) S(ampling) or MIDAS regression models to address the often encountered in practice issue of the applicable information being high-frequency data, while the measure of interest being a low-frequency process – an approach firstly put forward by Ghysels, Santa-Clara, and Valkanov (2004). In their study, they showed that the tightly parameterized and flexible reduced form MIDAS regressions are always relatively more efficient than the classical temporal aggregation approach that discards the higher frequency information. The MIDAS regression model is, in part, related to the traditional temporal aggregation literature that for decades has been studying the consequences of the classical temporal aggregation approach. For instance, the analysis of Engle

and Liu (1972) focuses on the bias in the average lag stemming from aggregation over time. The effects of temporal aggregation were discussed also by Brewer (1973), Geweke (1978), and Hsiao (1979), among many others. Although both the MIDAS regression model and the traditional temporal aggregation literature investigate the consequences of traditionally time-aggregating the data, the MIDAS technique allows for data to be sampled at different frequencies by attributing different weights to each high-frequency observation. Overall, the traditional temporal aggregation approach is restricted and thereby a data-driven aggregation scheme should be applied when estimating econometric models.

Following the MIDAS development by Ghysels et al. (2004), the literature has been extensively enhanced with the MIDAS regression models suggesting that they yield improved inferences vis-à-vis traditional models, such as improved forecasts, and testing results, among others. Armesto, Engemann, and Owyang (2010) suggested MIDAS models as a solution to the equal weighting scheme and parameter proliferation problems stemming from the simple time-averaging method and the step weighting function, respectively, as well as a more beneficial forecasting tool especially when intra-period data are used. The benefits from estimating MIDAS regression models with different weights rather than estimations based on an equal weighting scheme are also revealed in Andreou, Ghysels, and Kourtellos (2010), where is technically and empirically shown that the slope estimator based on a flat aggregation scheme (FLAT-LS) is always relatively less efficient than the MIDAS Nonlinear Least Squares (MIDAS-NLS) estimator. Importantly, the slope regression estimator is both asymptotically biased and inefficient when the high-frequency predictors follow an Autoregressive AR(1) process. Similarly, in the study of Andreou (2016), it is shown that there is a bias of the LS slope regression estimator when a flat weighting scheme is applied instead of a non-flat when the Data Generating Process (DGP) is a MIDAS model, while effective volatility forecast is achieved by measuring intra-daily squared returns using forecasting variables available at very high frequencies (e.g. daily). Forecasting volatility based on high-frequency information through the MIDAS models was also studied by Ghysels and Valkanov (2012) showing that in general, MIDAS forecasts exhibit a relatively good balance concerning bias and estimation efficiency.

Our contribution is new empirical evidence, showing that when the low-frequency process is the GDP growth in the European Union (EU) and the high-frequency information is either Survey, Confidence Indicators (CIs) of firms and consumers in the EU, or other Financial Indicators (FIs) commonly used in the literature, estimating a MIDAS model instead of a standard Linear Least Squares (LS) model yields a slope regression estimator with statistically significant higher impact, i.e. bias of the slope regression estimator in the common frequency model, and with statistically significant forecasting gains. Besides the in-sample and out-of-sample improvements of the MIDAS models compared to traditional aggregation approaches which are obtained based on the use of high-frequency 'soft' survey and financial data, our analysis reveals the prominent role of the Consumption Sentiment Indicator as a predictor of the EU economic outlook – evidence shown both in-sample and out-of-sample based on bias and efficiency principles.

The motivation behind the use of the so-called 'soft' survey and financial indicators – predictors that are timely made public, is wide-ranging. For instance, Angelini et al. (2011) showed the beneficial use of survey data and other soft information in nowcasting the euro area GDP growth through bridging via factors. Their methodology, however, bridges the monthly soft information using quarterly aggregation techniques that employ an equal weighting scheme to each higher frequency monthly observation. The substantial role of survey and financial data in

forecasting the euro area GDP growth is also addressed in Bánbura and Rünstler (2011). In particular, when the more-timely publication of the data is taken into account GDP forecasts are more accurate than those based on hard data that are made public with a delay. Their approach differs from our approach as it is based on a Dynamic Factor Model (DFM) where the Kalman filter deals with missing observations and a new monthly series is constructed to incorporate quarterly GDP growth into a monthly state space representation. Similarly, based on a factor approach to deal with ragged edges, mixed frequencies, and data revisions for GDP growth, Camacho and Perez-Quiros (2010) showed that business surveys gain importance compared to hard economic activity data in short-term forecasts of the euro area GDP growth, once the timeliness of surveys is considered. On the other hand, in the study of Girardi, Gayer, and Reuter (2015) it is shown that through a factor approach that blocks/distributes monthly observations into specific quarterly series, timeliness is not the only quality of survey data in nowcasting the Euro Area-wide GDP growth, while the vital role of financial indicators is investigated, especially during crisis periods, such as that of the Great Recession. Noteworthy examples of the great use of financial predictors in forecasting exercises consist of the analysis of Andreou, Ghysels, and Kourtellos (2013), Monteforte and Moretti (2013), and Ferrara and Marsilli (2013), among others. Analytically, the study of Andreou et. al (2013) shows that through MIDAS estimations based on daily financial information, forecasts of the GDP growth in the United States are more accurate when high-frequency daily financial information is exploited rather than low-frequency quarterly macroeconomic information. Similarly, MIDAS estimations based on high-frequency financial data reduce forecast errors of euro area inflation compared to standard VAR models using lower frequency data (Monteforte and Moretti, 2013). In addition, the relatively good predictive power of major financial variables and in particular that of stock prices by comparison with the soft Economic Sentiment Indicator (ESI) in predicting the euro area GDP growth is documented through a MIDAS approach in the work of Ferrara and Marsilli (2013). Furthermore, asset price data through MIDAS and Kalman filter techniques were used by Ghysels and Wright (2009) to form daily forecasts of upcoming survey releases.

It is worth mentioning that, the majority of the soft survey and financial series considered in our analysis are frequently used as components to compose Leading Economic Indexes by several economic organizations and institutions, with the Stock Price Index and the Consumption Confidence Indicator being the most common constituents compared to other financial and survey indicators, respectively. See, for instance, the components of the CB Leading Economic Index for the US, the Euro Area, France, Germany, and the UK, as well as those of the OECD Composite Leading Indicator for France. Additionally, in the study of Bondt and Hahn (2014) and Tkacova, Gavurova, and Behun (2017), both the Stock Price Index and the Consumption survey indicator were used to construct a Leading Economic Indicator for the euro area and Germany, respectively. Constructing Leading Indicators for the economy and stressing the role of both the total Index and its components in forecasting key macroeconomic variables consists a large literature in economics. For instance, the forecasting performance of the US CB Composite Leading Indicator's components including the term spread, the Stock Price Index, and the Michigan Consumer Confidence Index, among others, in forecasting the US output growth were assessed through MIDAS estimations with multiple regressors in Clements and Galvão (2009). The Consumer Sentiment combined with other surveys, interest rates, and monetary aggregates were also considered in the analysis of Kuzin, Marcellino, and Schumacher (2011) to provide a comparison between the MIDAS and the mixed-frequency VAR models. A more detailed

discussion about the soft survey and financial data enhanced in our analysis is provided in the relevant empirical section of the paper.

Our analysis is novel in terms of proofing the significant role of the Consumption Sentiment Indicator compared to other sentiments as well as compared to classical financial predictors in projecting the economic outlook of the European Union through MIDAS regressions. More specifically, we show that when estimating a standard common frequency Linear-LS univariate model, the overall Economic Sentiment Indicator (ESI) brings the best-fitted model in terms of information criteria, as well as the best out-of-sample predictor in terms of forecasting errors compared to all sentiments averaged to compose the ESI, whereas, not such finding is concluded in the mixed data sampling analysis. In particular, when estimating a MI(xed) DA(ta) S(ampling) – MIDAS univariate model, the Consumption Sentiment Indicator brings both the best-fitted model in terms of information criteria and the best out-of-sample predictor in terms of forecasting errors, compared to all the other sentiments averaged to compose the ESI as well as the total sentiment index, regardless of the MIDAS weighting scheme. Importantly, when classical financial predictors are included in the analysis, the Consumption Sentiment Indicator provides more accurate forecasting results for the EU GDP growth than the best-in-sample and out-of-sample financial predictor – the Stock Price Index. In more detail, although the Stock Price Index brings the best-fitted model in terms of information criteria and the best out-of-sample predictor in terms of forecasting errors among all financial predictors, when all soft survey and financial predictors are evaluated, the Consumption Confidence Indicator domains. Although the standard Linear-LS model is in favour of the Stock Price Index predictor, the majority of the MIDAS models are in favour of the Consumption Sentiment Indicator predictor, in terms of forecasting errors. Then, comparing the 'best' Linear-LS single-variable model with the 'best' MIDAS single-variable model, the mixed-frequency model outperforms the common-frequency model and thereby the 'best' sentiment predictor (Consumption Sentiment Indicator) outperforms the 'best' financial predictor (Stock Price Index). Subsequently, our analysis not only reveals the benefits of using mixed-frequency vis-à-vis traditional temporal aggregation approaches, but also the vital role of the Consumption Confidence Indicator in explaining and forecasting key macroeconomic variables such as GDP growth through MIDAS regressions – a finding which would not have been revealed if the common- instead of the mixed-frequency model had been estimated.

The paper is organized as follows. In Section 2 we outline possible methods of forecasting a quarterly low-frequency macroeconomic variable such as GDP growth using soft survey and financial monthly indicators as predictors. The common-frequency and mixed-frequency MIDAS models considered are portrayed and the discreet relationship between the different frequency-type models is delineated. A comprehensive description of the soft survey and financial data employed in our empirical analysis is provided in Section 3 where the in-sample and out-of-sample estimation results when soft survey confidence and financial indicators are used as higher frequency explanatory variables in the mixed-frequency MIDAS regressions are assessed. The empirical analysis is with regard to the European Union (EU) economy. Section 4 includes the robustness section which evaluates the estimation outcomes incurred from the corresponding models analysed in Section 3 focusing on the Spain (ES) and the United Kingdom (UK) economies. As a final point, Section 5 indicates a set of summarized conclusions demonstrating the pros of MIDAS estimations compared to conventional aggregation approaches, as well as the valuable role of the Consumer survey as a predictor for the European economy.

2. Regression models of a low-frequency macroeconomic variable with higher frequency 'soft' predictors

This section states the different types of models considered in our analysis and the low-key relationship between them. The common-frequency model is an Autoregressive Distributed Lag (ADL) regression model where the high-frequency soft predictors, x_t^H, are embedded in the model through conventional aggregation approaches (averaging the higher frequency data). The mixed-frequency model is a MI(xed) DA(ta) S(ampling) – MIDAS regression model where the response to the higher frequency soft data, x_t^H, is modeled through parsimonious weighting schemes.

2.1. Common-frequency and mixed-frequency models

The basic single common-frequency regressor $\boldsymbol{ADL(p,q)}$ model for forecasting one quarter ahead the low-frequency macroeconomic variable, y_t^L, is given by:

$$y_{t+1}^L = \alpha + \sum_{i=1}^{p} \lambda_i L^i y_t^L + \sum_{j=1}^{q} \lambda_j L^j x_t^L + \varepsilon_{t+1}^L, \tag{2.1}$$

which involves p lags of the low-frequency macroeconomic variable y_t^L and q lags of the aggregated high-frequency soft variable x_t^L in accordance with information criteria and serial correlation tests. It is obvious that, the $ADL(p,q)$ univariate model provides a direct forecast of the low-frequency macroeconomic variable one quarter ahead, y_{t+1}^L, based on p lags of the low-frequency macroeconomic variable, y_t^L, and q lags of the temporally aggregated high-frequency soft variable, x_t^L, where L^k is the lag operator and $k = 1, \dots K$. Although it might be a simple approach that allows for only $p + q + 1$ estimated regression coefficients, imposing equal weights on the high-frequency observations through the aggregation procedure causes loss of information. For instance, attributing equal weights on the monthly soft data, that is, $x_t^L = (x_{1,t}^H + x_{2,t}^H + x_{3,t}^H)/3$, might not be optimal as time series data are expected to exhibit memory decay with a descending sloping form amid the more beneficial recent information in forecasting exercises. Assume now that we are interested in using the monthly observations of the soft predictors rather than their quarterly observations. In that case, the single high-frequency regressor $\boldsymbol{ADL\text{-}MIDAS(p,q)}$ model for forecasting h-steps the low-frequency macroeconomic variable, y_t^L, considered is:

$$y_{t+h}^L = \alpha_h + \sum_{i=1}^{p} \lambda_{h,i} L^i y_t^L + b_h \sum_{k=1}^{K} w(k;\theta_h) L^{k/m} x_t^H + \varepsilon_{t+h}^L, \tag{2.2}$$

where the flexible data-driven weighting scheme, $W\left(L^{1/m};\theta\right) = \sum_{k=1}^{K} w(k;\theta) L^{k/m}$, considers the time-series behaviour of the data by allowing for different weights to be assigned to each high-frequency monthly observation and with only a small number of hyperparameters, θ, to be estimated. The number of months per quarter and the maximum number of high-frequency monthly lags are denoted by m and K, respectively. Following Clements and Galvão (2008), we allow for lags of the low-frequency macroeconomic variable since ADL-MIDAS models were found to outperform the Distributed Lag MIDAS (DL-MIDAS) models without low-frequency augmentations. Likewise the $ADL(p,q)$ model, the $ADL\text{-}MIDAS(p,q)$ model provides a direct forecast of the low-frequency macroeconomic variable h-steps ahead, y_{t+h}^L, based on lags of the low-frequency macroeconomic variable, y_t^L, and lags of the high-frequency soft variable, x_t^L, where L^j and $L^{j/m}$ are lag operators for the low- and high-frequency data, respectively. Note that, adding all the high-frequency weights gives a sum equal to one, $W(1;\theta) = \sum_{k=1}^{K} w(k;\theta) = 1$.

Parameterizing the lagged coefficients $w(j;\theta)$ is a key feature of the MIDAS models as it provides solution to the parameter proliferation problem where a potentially large number of parameters needs to be estimated. There are several potential parameterizations of the MIDAS weighting scheme with the majority of them being considered in our empirical analysis. A MIDAS weighting function with only few parameters to be estimated and considered in our analysis is the Beta function which is closely related to the Gamma function:

$$y_{t+h}^{L} = \alpha_h + \sum_{i=1}^{p} \lambda_{h,i} L^i y_t^L + b_h \sum_{k=1}^{K} [\frac{z_k^{\theta_1-1}(1-z_k)^{\theta_2-1}}{\sum_{j=0}^{K} z_j^{\theta_1-1}(1-z_j)^{\theta_2-1}} + \theta_3] L^{k/m} x_t^H + \varepsilon_{t+h}^L, \quad (2.3)$$

where $z_i = i/K$ and K is the maximal MIDAS polynomial lag. Note that, all three MIDAS parameters $(\theta_1, \theta_2, \theta_3)$ are included in the underlying model to avoid the bias that might be generated when imposing the zero endpoint restriction $(\theta_3 = 0)$. An alternative MIDAS weighting scheme with only few parameters to be estimated is the MIDAS regression model with exponential Almon lags. Following Ghysels, Santa-Clara, and Valkanov (2006), we allow for a flexible data-driven scheme using only two parameters (θ_1, θ_2) in the exponential Almon lag polynomial:

$$y_{t+h}^{L} = \alpha_h + \sum_{i=1}^{p} \lambda_{h,i} L^i y_t^L + b_h \sum_{k=1}^{K} [\frac{exp(\theta_1 k + \theta_2 k^2)}{\sum_{j=0}^{K} exp(\theta_1 j + \theta_2 j^2)}] L^{k/m} x_t^H + \varepsilon_{t+h}^L. \quad (2.4)$$

Both the Beta function and the exponential Almon lag function are flexible parsimonious parameterizations where the weights might take several shapes; either exhibit a hump shape, decline slowly, or decline quickly. Hence, the number of high-frequency lags to be included in the regression model can be determined by specific parameterizations that allow different values for the parameters (estimated from the data) and settle the shape of the weights (Ghysels and Marcellino, 2018). As it can be seen, the parameters, $(\alpha_h, \lambda_{h,1}, \dots, \lambda_{h,p}, b_h, \theta_1, \theta_2, \theta_3)$, of both the MIDAS regression model with beta weights and with exponential Almon lags in equations (2.3) and (2.4), respectively, are estimated by nonlinear least squares.

It should be mentioned that the exponential Almon lag specification is closely related to the natural candidate parameterization for dealing with mixed-sampling frequencies – the MIDAS regression model with Polynomial Distributed Lags (PDL). In the case of a PDL MIDAS specification, the number of lags to be estimated depends on the degree of the polynomial, l, rather than the number of high-frequency lags. More specifically, for each high-frequency lag up to the maximum number of high-frequency lags, K, the high-frequency soft coefficients are estimated as a lag polynomial of order l in the MIDAS parameters, θ_i:

$$y_{t+h}^{L} = a_h + \sum_{i=1}^{p} \lambda_{h,i} L^i y_t^L + \sum_{k=0}^{K} x_{t-k/m}^{H\,\prime} \left(\sum_{j=0}^{l} k^j \theta_j\right) + \varepsilon_{t+h}^L. \quad (2.5)$$

Last but not least, our analysis includes the MIDAS specification that is known to trigger the parameter proliferation problem – the MIDAS regression model with unrestricted coefficients (UMIDAS) proposed by Foroni, Marcellino, and Schumacher (2015). Nevertheless, this is not our case. That is, the differences in sampling frequencies between the low-frequency macroeconomic variable and the high-frequency soft predictor are small; the low-frequency economic indicator is available at quarterly frequency and the high-frequency soft survey/financial predictor is available at monthly frequency. Foroni et. al (2015) correspondingly showed that UMIDAS regression models outperform MIDAS regressions estimated by nonlinear least squares when nowcasting and forecasting the low-frequency GDP growth in the US using monthly indicators. The

unrestricted MIDAS model does not depend on lag polynomials like the PDL MIDAS specification and it can be thus estimated by ordinary least squares:

$$y_{t+h}^{L} = a_h + \sum_{i=1}^{p} \lambda_{h,i} L^i y_t^L + \sum_{k=0}^{m\widetilde{K}} w_{h,k} x_{t-k/m}^{H} + \varepsilon_{t+h}^{L}, \quad (2.6)$$

where $\widetilde{K}$ is such that the error term, ε_{t+h}^{L}, is uncorrelated and the parameter proliferation problem is absent. Equation (2.6) shows that indeed in the case of a UMIDAS model an OLS estimation can be applied, compared to a typical MIDAS regression model where nonlinear least squares approximations are used for estimating the parameters (Ghysels and Qian, 2019). For simplicity, the MIDAS specifications considered in our empirical analysis; BMIDAS, EMIDAS, PMIDAS, and UMIDAS stand for MIDAS regressions with beta weights, MIDAS regressions with exponential Almon lags, Polynomial Distributed Lag MIDAS regressions, and MIDAS with unrestricted coefficients, respectively. Note that, the alternative specifications of MIDAS regression polynomials are comprehensively discussed in Ghysels, Sinko, and Valkanov (2006) including the MIDAS regressions with step functions. Our empirical analysis considered almost all weighting MIDAS schemes to capture the advantages of the MIDAS models, in-sample and out-of-sample, compared to the Linear-LS model regardless of the weighting function considered. In unreported implementations, we have experimented also the MIDAS regression with step functions without finding any in-sample and out-of-sample improvements compared to the above mentioned MIDAS models employed in our analysis. A possible explanation is the same estimated slope coefficient assigned to several monthly soft observations that belong to a "group" corresponding to the size of the step function.

The decision on the optimal number of lags of the low-frequency macroeconomic variable and of the high-frequency soft predictor in the common-frequency model is as already mentioned based on information criteria including the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the Hannan–Quinn information criterion (HQC). Our selection procedure, however, is mainly based on the BIC criterion developed by Schwarz (1978) due to the more robust outcome provided amid its more extensive penalty term. Notably, serial correlation tests are applied to confirm the selection criteria further. A corresponding selection approach is applied in the unrestricted MIDAS regression estimated by ordinary least squares that does not resort to distributed lag polynomials. Interestingly, when it comes to the optimal lag selection in the mixed-frequency model estimated by nonlinear least squares, besides the information criteria and serial correlation analysis, the distribution of the weights contributes to determining the optimal number of lags of the high-frequency soft predictor. Note that, the inclusion of augmentations of the low-frequency variable allows us to select the optimal number of lags based on information criteria, which is why Andreou, Ghysels, and Kourtellos (2013) considered an information criterion in the selection procedure (Ghysels and Marcellino, 2018).

2.2. Relationship between ADL and ADL-MIDAS regression models

The MIDAS regression model is, to a certain extent, related to the traditional temporal aggregation literature. Both have been extensively used to analyze the consequences of temporally aggregating high-frequency data to obtain the same low-frequency for all series (see for example Andreou, Ghysels, and Kourtellos (2010)). The low-key relationship between the common-frequency model (based on the traditional temporal aggregation approach) in Equation (2.1) and the mixed-frequency MIDAS model (based on a weighting scheme) in Equation (2.2) is revealed in the subsequent stage. To begin with, the conventional aggregation procedure employed in Equation (2.1) has the restriction of imposing the same weights on the high-

frequency observations, $(x_{1,t}^H + x_{2,t}^H + x_{3,t}^H)/3$. In particular, the estimated slope coefficient of the temporally aggregated high-frequency soft variable, λ_k, in Equation (2.1) contains the portion $1/m$ that is assigned to each high-frequency observation being aggregated, discarding any evidence about the timing of innovations to higher frequency data. Following Andreou, Ghysels, and Kourtellos (2013), the weighting scheme λ_k/m can be referred as the *flat aggregation scheme*, which has been extensively used in the conventional temporal aggregation literature. The relationship between the two equations is made more obvious when writing Equation (2.2) as follows:

$$y_{t+h}^L = \alpha_h + \sum_{k=1}^{p} \lambda_{h,k} L^k y_t^L + \sum_{k=1}^{q} b_{h,k} L^k x_t^L(\tilde{\theta}_h) + \varepsilon_{t+h}^L, \tag{2.7}$$

where the quarterly soft variable is in terms of MIDAS hyperparameters, $x_t^L(\tilde{\theta}_h) \equiv \sum_{j=1}^{m} w(j;\tilde{\theta}) x_t^H$. On the whole, the traditional temporal aggregation approach is restricted and a data-driven aggregation scheme that determines the shape of the weight distribution should be applied when estimating econometric models with mixed frequency data. As such, our analysis aims to reveal the existence of *bias* when estimating a common-frequency Linear Least Squares (LS) model instead of the mixed-frequency MIDAS regression model. To show the existence of bias, we test the null hypothesis of a flat aggregation scheme H_0: $\theta = 0$, i.e. equal weighs of the high-frequency observations, in Equation (2.2). Since the term bias refers to the omitted important information coming from the higher frequency observations that is neglected when temporal aggregation approaches are applied, standard tests for a conditional mean zero can be applied. Following Andreou, Ghysels, and Kourtellos (2010), we directly test the flat aggregation scheme by applying the simple Lagrange Multiplier (LM) test:

$$LM = T(SSR_0^{LS} - SSR_1^M)/SSR_0^{LS} \xrightarrow{d} \chi^2(r), \tag{2.8}$$

where SSR_0^{LS} indicates the sum of squared errors from estimating the common-frequency model based on equal weights, (2.1), and SSR_1^M the sum of squared errors from estimating the mixed-frequency MIDAS model based on a data-driven weighting scheme, (2.2). The LM statistic is often used in the literature for model evaluation and comparison purposes. For instance, it was used by Lundbergh and Teräsvirta (2002) for testing the null hypothesis of no ARCH in standardized errors, linearity, and parameter constancy against smoothly altering parameters. Similarly, Conrad and Schienle (2020) used the direct LM test for the null hypothesis that the omitted multiplicative long-term component in the GARCH models has no explanatory power. The LM statistic of Conrad and Schienle (2020) was employed also by Conrad and Kleen (2020) to test for misspecification in one-component GARCH models in the view of a neglected second (multiplicative) component. Their empirical results using the LM test put forward the use of GARCH-MIDAS models instead. In our study, the LM statistic is used to test the flat weighting scheme in the mixed-frequency MIDAS models when the high-frequency predictors are soft survey or financial indicators. If the test rejects the null hypothesis of a flat aggregation scheme, then there is bias when estimating the ADL model rather than the ADL-MIDAS model amid the significant high-frequency information that is discarded. The soft survey and financial data used in our empirical analysis are discussed in more detail in the next section.

3. Empirical Analysis

In this section, we implement an in-sample and out-of-sample analysis using the MIDAS models when the low-frequency quarterly variable is Real GDP growth in the European Union (EU) and the higher monthly frequency soft Confidence Indicators (CI) and Financial Indicators (FI) are used as predictors. Our main objectives are to bring to light the in-sample and out-of-sample pros of the MIDAS models compared to common-frequency models according to bias and efficiency principles. In particular, we want to reveal the statistically significant higher impact of the estimated slope coefficient (*bias*) when a MIDAS model is estimated instead of a Linear-LS model (based on temporal aggregation), as well as the *forecasting gains* of the MIDAS models compared to both the Linear-LS models and other traditional benchmark models used in the literature, including the Autoregressive (AR(p)) and Random Walk (RW) models. Remarkably, our analysis discloses the protuberant role of the Consumption Sentiment Indicator as predictor of the EU economic outlook – an evidence shown both in-sample and out-of-sample based on bias and efficiency principles.

3.1. Data Description

The low-frequency macroeconomic variable to be forecasted in our analysis is a regular indicator of economic activity, and more specifically, the GDP growth in the European Union – a relatively small economy (compared to the US). Note that, a robustness section is included in our analysis that provides a corresponding empirical analysis for some individual countries composing the EU, including Spain and the United Kingdom (our sample does not include the Brexit event). The data used in our analysis capture the period starting from 1995Q1 to 2019Q4 so as to exclude the COVID-19 pandemic crisis from the sample. In the general case where the policymaker is interested in tracking the current state of the economy and its expected prospects, measures aside from GDP growth are available at the time of evaluation. For example, the policymaker might consider composite economic indicators using their leading and concurrent estimates and other survey confidence indicators, e.g. the Economic Sentiment Indicator (ESI), which are publicly available without delay, as well as commodity and stock prices (financial indicators) that are available at very high frequencies, such as daily. These indicators can construct a forecast of the current state of the economy without having to use delayed publicly available measures of the economy. As such, our analysis studies the unique role of several survey and financial soft indicators in monitoring and forecasting the EU economic outlook. It is worth pointing out that, following Bánbura and Rünstler (2011) surveys and financial series are the so-called '*soft*' indicators that are timely available and can reflect market expectations, whereas 'hard' indicators refer to real activity data that even though directly reflect macroeconomic fluctuations, are available with a weighty delay.

The soft survey predictors considered in our analysis are the Economic Sentiment Indicator (ESI) and its five sectoral confidence components, while the analysis using the questions of each specific confidence indicator is also provided. ESI is an adjusted weighted average of responses to directed designated questions to firms and households embraced by the EU Business and Consumer Surveys, where the sectors encompassed are the industry sector with the highest weight (40%), the services with the second highest weight (30%), consumption with a weight of 20%, and lastly retail and construction sectors with the lowest weight (each 5%). All sectors consist of questions that are related to economic and financial situations over the past, current, and next months. Notably, only the Consumption CI's questions depict expectations for the next 12 months, whereas for all the other sectors questions capture expectations about the next 3 months. This is an initial indication of the strong leading ability of the Consumption CI relative to the other sectors. Regarding the financial soft series, our analysis considered the commonly used

stock price leading indices in the literature, i.e. the total market Euro Stoxx Price Index and the subset Euro Stoxx 50 Price Index that represents the 50 largest (free-float market cap) corporations in the midst of 20 supersectors in countries of the euro area, the classical Government Benchmark Bond Yield – the Germany 10-year bond yield, several Euro Interbank Offered Rates (Euribor), as well as commodity and hard metal prices that are vital for the global market expectations. The Euribor interest rates at which various European banks borrow funds could not be neglected from our empirical analysis as they consist among the most important indication rates within the European money market. Among the five available Euribor interest rates, our analysis includes the ones with the longest horizons; Euribor rates with a maturity of 3 months, 6 months, and 12 months. In addition to the important money market interest rates, commodity prices are also included in our analysis stressing the effect of several sectors (energy, precious metals, and agriculture) on economic growth. More specifically, the explicit role of the Brent Crude oil price, the West Texas Intermediate (WTI) oil price, and the Crude Oil futures contracts is evaluated within the energy sector, the prices of the gold and silver precious metals, as well as the corn and wheat prices within the agriculture sector. Stressing the role of commodity prices on economic activity is important due to the significant risks that fluctuations on commodity prices might pose on the economic performance globally.

An essential step in our analysis is that all variables needed to be transformed before estimation in order to be stationary, which is also a very important assumption for time-series data. Transformations include the first differences and log differences of the series. For the GDP, stock, and commodity time series, logarithmic differences have been applied, while for the interest rates and spreads, as well as the survey data, the first differences have been applied. Note that, for comparison purposes between the different regression models, all series (transformed) were standardized before estimation. Table 1 in the Appendix represents information about the variables used in our models regarding their acronyms, definition, sources, frequency and the transformations applied. Next, analysis regarding the correlation (at time t) between the GDP growth and the Confidence or Financial Predictors for both the EU, ES, and the UK is implied. Table 2a, Table 2b, and Table 2c of the Appendix represent the correlation between the GDP growth and the CI and FI for the EU, ES, and UK, respectively. The association between the independent variables is also provided in the matrices. It can be seen that, among all the Confidence Indicators, EU Building Confidence Indicator has the highest correlation with EU GDP growth, while, Euribor 3-month and 6-month rates are the most associated indicators with EU GDP growth among all the Financial Indicators. Correspondingly, the correlation matrix for ES indicates that, among all the Confidence Indicators, the ES Industry Confidence Indicator has the highest correlation with ES GDP growth, while like in the EU case, among all the Financial Indicators, the Euribor interest rates seem to exhibit the highest correlations with ES GDP growth. Regarding the UK correlations, likewise the EU case, the UK Building Confidence Indicator has the highest correlation with UK GDP growth, whereas, in contrast to the EU and ES cases, the stock prices exhibit the highest correlation with the UK GDP growth. Hence, the building and industry Confidence Indicators and the Euribor and Stock Financial Indicators seem to exhibit relatively good comovements with GDP growth regarding the EU, ES, and UK economies. It is worth mentioning that in unreported exercises, Pearson correlation coefficient analysis shows signs of leading ability for all soft survey and financial indicators considered in our analysis. Descriptive statistics about explanatory variables, both Confidence Indicators (CI) and their questions in the EU and Financial Indicators (FI) are also represented through a set of tables in Appendix. It is noted that descriptive statistics about CI are provided not only for the EU but also for Spain (ES) and the United Kingdom (UK) following the robustness analysis of some of the EU's member states.

3.2. Empirical Models – The EU case

3.2.1. The role of Survey Confidence Indicators (CIs)

Our first objective is to appraise the unequivocal role of Survey Confidence Indicators in describing and anticipating movements in the EU GDP growth through both common and mixed frequency models. The in-sample estimation results of quarterly EU GDP models are reported in Table 1. This table indicates the estimation results of the Linear-LS regression model with common frequency variables (based on conventional aggregation techniques) vis-à-vis the alternative MIDAS models with predictors sampled at a higher monthly frequency with the intention to reveal the *bias* incurred when a Linear-LS model is estimated instead of a Mixed Data Sampling (MIDAS) model. In the table are reported the estimated slope coefficient of the GDP growth, $\hat{\beta}_{GDP}$**,** the estimated slope coefficient of each CI, $\hat{\beta}_{CI}$, the BIC for each single-variable model (estimate GDP growth using sentiment indicators as predictors one at a time), as well as the LM statistic. The estimated slope coefficient of each confidence predictor in both the Linear-LS models and the NLS-MIDAS models with beta and exponential Almon weights is estimated within the regression. For the PMIDAS and UMIDAS models, the slope coefficient is computed as the sum of the estimated monthly lags of each CI where the significance of the slope coefficient is taken as the significance of the most important lag among the estimated polynomials and lags.

Markedly, the models presented in the table are the best models according to the information criteria; the augmentations of GDP growth that compose the estimated slope coefficient of GDP growth and the number of lags of each sentiment predictor that compose the estimated slope coefficient of the CI are such that provide the best-fitted models for each single-variable model. Analytically, lags of both the GDP growth and the CI were chosen on the basis of a 'General to Specific' approach. Our General Unrestricted Model (GUM) – an Autoregressive Distributed Lag (ADL) model included four lags of GDP growth and four lags of the survey predictor when the common frequency is quarterly, incorporating maximum the last year of quarterly data. Considering the statistical significance of the predictors, the minimum BIC criterion, and serial correlation tests, among others, we ended up with a smaller yet more parsimonious model. Analogously, in the case where the survey predictor is available at a higher sampling frequency such as monthly, the GUM – a MIDAS regression model included 12 monthly lags of the survey predictor and four quarterly lags of GDP growth so that the model incorporates maximum the last year of monthly and quarterly data. Considering the statistical significance of the predictors, the minimum BIC criterion, serial correlation tests, as well as the distribution of the high-frequency weights, we ended up with a smaller, still more parsimonious model. Note that, in the case of estimating the AR(p) quarterly-frequency benchmark model, the maximum number of GDP augmentations was, in the same way, equal to four.

The MIDAS weighting functions considered in our analysis are, as already stated, the beta weights (BMIDAS), the exponential weights (EMIDAS), the polynomial Almon weights (PMIDAS), and the MIDAS models with unrestricted coefficients (UMIDAS). The single-variable models are reported in the table in priority order according to their BIC value, i.e. the model with the lowest BIC value is listed first. Remarkably, when a mixed-frequency MIDAS model is estimated, the model using the Consumption CI brings the best-fitted model in terms of the BIC criterion compared to all other models considering other sentiments as predictors, irrespective of the weighting function employed. Notably, there is a robust pattern regarding the order of the mixed-frequency models; consumption, ESI, and industry surveys bring the three best-fitted models (in

terms of the BIC value), unrelatedly of the MIDAS aggregation scheme. On the other hand, the Economic Sentiment Indicator (ESI) brings the best-fitted model in terms of the BIC criterion compared to the models using other sentiment predictors when considering common sampling frequencies.

Table 1: In-sample estimation results (1995Q1-2019Q4) of the MIDAS regression models when low-frequency variable is quarterly EU GDP and high-frequency predictors are monthly Confidence Indicators (CIs) vis-à-vis the corresponding common-frequency Linear-LS models.

	Monthly Frequency of Confidence Indicator (CI)							
	BMIDAS				**EMIDAS**			
	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CI}}$	**BIC**	**LM**	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CI}}$	**BIC**	**LM**
EUCONS	0.439***	**0.221*** **	**0.033**	**0.000**	0.519***	0.177***	**0.031**	**0.000**
EUESI	0.507***	0.139***	0.078	**0.022**	0.453***	**0.185*** **	0.056	**0.025**
EUINDU	**0.580*** **	0.075	0.131	**0.094**	0.477***	0.139***	0.129	0.341
EUSERV	0.538***	0.125*	0.243	0.621	0.556***	0.136**	0.242	1.000
EURETS	0.552***	0.151	0.256	0.648	**0.563*** **	0.119	0.211	0.480
EUBUILD	0.496***	0.176*	0.254	1.000	0.533***	0.104***	0.226	1.000
	PMIDAS				**UMIDAS**			
	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CI}}$	**BIC**	**LM**	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CI}}$	**BIC**	**LM**
EUCONS	0.429***	**0.221*** **	**-0.009**	**0.000**	0.519***	0.177***	**-0.062**	**0.000**
EUESI	0.499***	0.147***	0.029	**0.020**	0.453***	**0.185*** **	-0.038	**0.007**
EUINDU	**0.580*** **	0.075**	0.085	**0.094**	0.477***	0.139***	0.035	0.143
EUSERV	0.538***	0.125***	0.196	0.621	0.573***	0.084**	0.153	1.000
EURETS	0.529***	0.201**	0.231	1.000	**0.578*** **	0.068***	0.141	1.000
EUBUILD	0.479***	0.158**	0.214	1.000	0.533***	0.104***	0.133	1.000
	Quarterly Frequency of Confidence Indicator (CI)							
	LINEAR							
	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CI}}$	**BIC**					
EUCONS	**0.540*** **	0.099***	0.119					
EUESI	0.406***	**0.158*** **	**0.038**					
EUINDU	0.392***	0.132***	0.057					
EUSERV	0.503***	0.138***	0.120					
EURETS	0.528***	0.101***	0.132					
EUBUILD	0.410***	0.139***	0.093					

***, **, ***: significance at 10%, 5%, 1% (two-sided p-values)*

***LM Test*:=** $T(SSR_0^{LS}\text{-}SSR_1^M)/SSR_0^{LS} \xrightarrow{d} \chi^2(r)$

Several important findings can be concluded from Table 1. First, the fitness of the model effectively improves when allowing for the higher frequency of the survey predictor rather than its low- quarterly frequency. For instance, the BIC value is 0.119 when the common-frequency model using consumption survey as a predictor is estimated, whereas it is appraised to be much smaller when the corresponding MIDAS model is estimated; it is 0.033, 0.031, -0.009, and -0.062 when BMIDAS, EMIDAS, PMIDAS, and UMIDAS models are estimated, respectively. The fitness of the model effectively improves when exploiting the higher frequency data of also other soft survey predictors beyond the Consumption CI. When the ESI is used as a predictor, the fitness improves estimating either a PMIDAS or a UMIDAS model rather than the corresponding Linear-LS model.

Similarly, when Industry CI is used as a predictor, the fitness improves estimating a UMIDAS model rather than the corresponding Linear-LS model. Second, when dealing with mixed sampling frequencies, Consumption CI brings the smaller BIC estimated value among all confidence indicators irrespective of the weighting function. For example, the estimated BIC value in the BMIDAS model considering the consumption survey as a predictor is 0.033, while considering other surveys as predictors such as the ESI, the estimated BIC value is larger (0.078). The significant role of the consumption CI is also revealed when looking at its estimated slope coefficient; it has among the largest estimated slope coefficients (0.221) – the largest effect on GDP growth compared to all other sentiments. As a consequence, both the estimated slope coefficient and the estimated BIC value show the vigorous in-sample role of consumption CI on GDP growth through the MIDAS regression models.

Beyond the improved fitness of the models and the disclosure of the significant role of the Consumption CI, our study indicates the bias of the estimated slope coefficient when a Linear-LS model is estimated vis-à-vis the corresponding MIDAS regression model. MIDAS estimations produce statistically significant larger estimated slope coefficients of the Confidence Indicators than the corresponding traditional Linear-LS model. More precisely, the estimated slope coefficient of the consumption CI in the Linear LS model is equal to 0.099, whereas, it is much greater when assessed in a MIDAS model; it is appraised to be 0.221 when BMIDAS and PMIDAS models are assessed, and 0.177 for EMIDAS and UMIDAS models. The bias is proved using the LM test in Equation (2.8) proposed in Andreou et. al (2010). In their analysis, they showed that there is bias considering a flat aggregation scheme instead of a non-flat exponential weighting scheme using the empirical Solow growth model. In our analysis, the estimations from the LM statistic show that for at least the first three best-fitted single-variable MIDAS models reported in Table 1 (with Consumption, ESI, and Industry as predictors), and especially for the MIDAS model with consumption survey as a predictor, there is significant omitted information when a Linear-LS model is estimated instead of the corresponding mixed-frequency model. It is worth mentioning that, there or thereabouts all Confidence Indicators are statistically significant in all kinds of models (BMIDAS and EMIDAS using retail survey and BMIDAS using industry survey are exceptions) and all cause a positive effect on Real GDP growth. Lastly, putting all estimation results together, the UMIDAS model with the Consumption predictor brings the best-fitted model among all kinds of models, irrespective of the sampling frequency and the MIDAS aggregation scheme applied. This is not an out-of-the-ordinary outcome as for example Barsoum and Stankiewicz (2015) showed that using a Markov-switching UMIDAS model compensates or outperforms the corresponding models with restricted polynomials in nowcasting and forecasting exercises for the US GDP growth. In the subsequent stage of our analysis, the good out-of-sample performance of UMIDAS models using Consumption CI as a predictor is demonstrated as well.

Overall, several useful results can be summarized from our in-sample empirical analysis using survey confidence indicators as predictors. To begin with, MIDAS models show that there is important information coming from the sentiment indicators which is disregarded when the common-frequency model is estimated instead of the corresponding mixed-frequency model (*bias*). Second, the fitness of the models substantially improves using the MIDAS models versus the corresponding Linear-LS models for several indicators. Lastly, the Consumption sentiment causes among the greatest impacts on GDP growth, while it brings the best-fitted model when a MIDAS model is estimated compared to the ESI predictor which brings the best-fitted model when a Linear-LS model is estimated.

The thought-provoking findings for the vital role of survey consumer sentiment in GDP growth led to a further in-sample analysis of consumptions' questions with the intention of probing the

role of each question used to compute to total Consumption Sentiment Indicator, separately, on GDP growth. The in-sample estimation results of quarterly EU GDP models are reported in Table 2. This table indicates the estimation results of the Linear-LS regression model with common frequency variables (based on conventional aggregation techniques) vis-à-vis the alternative MIDAS models with consumption predictors sampled at a higher monthly frequency with the intention to reveal the *bias* incurred when a Linear-LS model is estimated instead of a Mixed Data Sampling (MIDAS) model. In the table are reported the estimated slope coefficient of the GDP growth, $\hat{\beta}_{GDP}$**,** the estimated slope coefficient of each consumption question and the total consumption index, $\hat{\beta}_{CCI}$, the BIC for each univariate model (estimate GDP growth using consumer sentiment indicators as predictors one at a time), as well as the LM statistic. Likewise in Table 1, the models presented in Table 2 are the best models according to information criteria; the augmentations of GDP growth that compose the estimated slope coefficient of GDP growth and the number of lags of the consumer sentiment predictor that compose the estimated slope coefficient of the consumption predictor are such that provide the best-fitted models for each single-variable model.

Table 2: In-sample estimation results (1995Q1-2019Q4) of the MIDAS regression models when low-frequency variable is quarterly EU GDP and high-frequency predictors are monthly Consumer Confidence Indicators (CCIs) vis-à-vis the corresponding common-frequency Linear-LS models.

	Monthly Frequency of Confidence Indicator (CCI)							
	BMIDAS				**EMIDAS**			
	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CCI}}$	**BIC**	**LM**	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CCI}}$	**BIC**	**LM**
EUCONS	0.439***	0.221***	**0.033**	**0.000**	0.519***	0.177***	**0.031**	**0.000**
EUCONS_q1	**0.532*** **	0.240***	0.097	0.128	0.536***	0.237***	0.052	**0.062**
EUCONS_q2	0.471***	0.367***	0.142	**0.002**	0.488***	**0.295*** **	0.114	**0.001**
EUCONS_q4	0.480***	0.164***	0.119	**0.002**	0.527***	0.152***	0.098	**0.002**
EUCONS_q9	0.499***	**0.390** **	0.227	0.136	**0.584*** **	0.071***	0.223	0.497
	PMIDAS				**UMIDAS**			
	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CCI}}$	**BIC**	**LM**	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CCI}}$	**BIC**	**LM**
EUCONS	0.429***	0.221***	**-0.009**	**0.000**	0.519***	0.177***	**-0.062**	**0.000**
EUCONS_q1	**0.533*** **	0.236	0.049	0.123	0.519***	**0.257*** **	0.129	**0.080**
EUCONS_q2	0.518***	0.230***	0.104	**0.002**	0.557***	0.141***	0.068	**0.002**
EUCONS_q4	0.467***	0.164***	0.081	**0.003**	0.527***	0.152***	0.004	**0.000**
EUCONS_q9	0.489***	**0.442**	0.213	0.492	**0.584*** **	0.071***	0.130	0.237
	Quarterly Frequency of Confidence Indicator (CCI)							
	LINEAR							
	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CCI}}$	**BIC**					
EUCONS	0.540***	0.099***	0.119					
EUCONS_q1	0.524***	**0.122*** **	**0.062**					
EUCONS_q2	**0.578*** **	0.070**	0.168					
EUCONS_q4	0.549***	0.085***	0.135					
EUCONS_q9	0.567***	0.078***	0.144					

, **, *: *significance at 10%, 5%, 1% (two-sided p-values)*

***LM Test**:= T(SSR_0^{LS}-SSR_1^M)/SSR_0^{LS}* $\xrightarrow{d}\chi^2(r)$

The further analysis of consumptions' questions shows that bias of the estimated slope coefficient is still an issue for the common-frequency models. MIDAS estimations produce statistically significant larger estimated slope coefficients of the Consumption Confidence Indicators than the corresponding traditional Linear-LS model. More precisely, the estimated slope coefficient of the fourth question (general economic situation over next 12 months in the EU) used to construct the total Consumption CI in the Linear LS model is equal to 0.085, whereas, it is much greater when assessed in a MIDAS model; it is appraised to be 0.164 when BMIDAS and PMIDAS models are estimated, and 0.152 for EMIDAS and UMIDAS models. The bias is again proved using the LM test in Equation (2.8) proposed in Andreou et. al (2010). In our analysis, the estimations from the LM statistic show that for almost all questions/predictors used to compose the total Consumer Index, there is significant omitted information when a Linear-LS model is estimated instead of the corresponding mixed-frequency model. It is worth mentioning that, roughly all Consumer Confidence Indicators are statistically significant in all kinds of models (PMIDAS models using either the first or the ninth question are exceptions) and all cause a positive effect on Real GDP growth.

Bias is not the only issue that remained in the in-sample analysis with the subsets of consumer survey since the fitness of each single-variable MIDAS model seems to again improve vis-à-vis the corresponding estimated Linear-LS model (irrespective of the consumer questions used as predictors). For instance, the BIC value is 0.062 when the common-frequency model using the first consumer question (financial situation over last 12 months in the EU) as a predictor is estimated, whereas it is appraised to be much smaller when the corresponding MIDAS model is estimated; it is 0.049 and 0.052 when PMIDAS and EMIDAS models are estimated, respectively. The fitness of the model effectively improves when exploiting the higher frequency data of also for the other consumer questions. When either the second (financial situation over the next 12 months in the EU) or the fourth (general economic situation over the next 12 months in the EU) consumer questions are used as predictors, the BIC estimated value of each MIDAS model is smaller compared to the corresponding Linear-LS model. Similarly, when the ninth consumer question (major purchases over the next 12 months in the EU) is used as a predictor, the fitness improves by estimating the UMIDAS model rather than the corresponding Linear-LS model. Significantly, when dealing with mixed sampling frequencies, the total consumption index brings the smaller BIC estimated value among all consumer questions unrelatedly to the weighting function. This finding suggests using the total consumer index rather than one of its subsets to explain movements in GDP growth, while it should not be omitted from our statements that the UMIDAS model remains the dominant best-fitted model among all kinds of models, irrespective of the sampling frequency and the aggregation scheme applied.

3.2.2. Out-of-Sample Forecasting Performance of CIs

After the in-sample estimation analysis, the forecasting performance of Confidence Indicators for the GDP growth in the EU is being studied. With the intention to evaluate the accuracy of these forecasts, for the quarterly sample period 1995Q1-2019Q4, we use as a training sample the period 1995Q1-2007Q4 and as an evaluation samples the periods 2008Q1-2019Q4 and 2008Q4-2019Q4. It is noted that the choice of the out-of-sample period is related to the beginning of the financial crisis in 2007 which was accompanied by the collapse of the investment bank Lehman Brothers. The out-of-sample estimation results of quarterly EU GDP models when forecasting one-quarter ($h = 1$) and four-quarters ($h = 4$) ahead are reported in Table 3, which represent the ratios of Root Mean Squared Forecasting Errors (RMSFEs) of EU GDP growth between the five types of predictive models (LINEAR, BMIDAS, EMIDAS, PMIDAS, and UMIDAS) and the widely

used in the literature benchmark models. Autoregressive (AR(p)) and Random Walk (RW) models display the benchmark models. The p-values testing the null hypothesis of equal predictive ability between the Linear-LS model and the MIDAS models based on the Diebold-Mariano test (2002) are also indicated in Table 3. It should be mentioned that, the out-of-sample results are with regards the best-fitted models (in terms of the BIC criterion) chosen in the previously discussed section. The ratio of RMSFEs for each Confidence Indicator (CI) used in the models is computed as follows:

$$r_i = \frac{RMSFE_{predictive\ model,CI_i}}{RMSFE_{benchmark\ model}}$$

where i represents the CI used in the predictive model and $i = 1, \dots, 6$. When the ratio is lower than one, it means that the predictive model based on a given Confidence Indicator, i, outperforms the benchmark AR(p) or RW model and vice versa.

Table 3: Out-of-sample estimation results of the MIDAS regression models when low-frequency variable is quarterly EU GDP and high-frequency predictors are monthly Confidence Indicators (CIs) vis-à-vis the corresponding common-frequency Linear-LS models.

Ratios of RMSFEs when the benchmark model is the RW										
	LINEAR		**BMIDAS**		**EMIDAS**		**PMIDAS**		**UMIDAS**	
	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$
EUCONS	0.90	0.90	**0.81****	**0.80****	**0.85***	**0.82***	**0.81****	**0.80****	**0.85***	**0.82***
EUESI	**0.85**	**0.83**	0.89	0.84	0.88	0.83	0.90	0.87	0.88	0.83
EUINDU	0.86	0.83	0.92	0.87	0.91	0.87	0.92	0.87	0.91	0.87
EUSERV	0.92	0.87	0.93	0.89	0.99	0.94	0.96	0.92	0.98	0.90
EURETS	0.95	0.90	0.96	0.91	0.96	0.91	1.00	0.94	0.96	0.91
EUBUILD	0.89	0.86	0.89	0.87	0.93	0.88	0.89	0.86	0.93	0.88
Ratios of RMSFEs when the benchmark model is the AR(p)										
	LINEAR		**BMIDAS**		**EMIDAS**		**PMIDAS**		**UMIDAS**	
	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$
EUCONS	0.91	0.98	**0.82****	**0.87****	**0.85***	**0.89***	**0.82****	**0.86****	**0.86***	**0.89***
EUESI	**0.86**	**0.90**	0.90	0.91	0.89	0.90	0.91	0.94	0.89	0.90
EUINDU	0.87	0.90	0.93	0.94	0.92	0.94	0.93	0.94	0.92	0.94
EUSERV	0.93	0.94	0.94	0.96	1.00	1.02	0.97	1.00	0.99	0.98
EURETS	0.96	0.97	0.97	0.99	0.97	0.98	1.01	1.02	0.97	0.98
EUBUILD	0.90	0.93	0.89	0.94	0.94	0.95	0.90	0.93	0.94	0.95

**: p-values of the Diebold-Mariano test*

From the out-of-sample estimation results it turns out that almost all models are able to outperform both benchmark models with Services and Retail Confidence Indicators being an exception when a MIDAS model (with exponential Almon or polynomial weights) is estimated. In all cases, Consumer, ESI, Industry, and Building surveys provide a ratio lower than one, $r_i < 1$, and thus are considered to be good out-of-sample predictors. In particular, the Consumption CI brings the best out-of-sample predictor among those in the table with the lowest RMSFE when a mixed-frequency MIDAS model is estimated (irrespective of the aggregation scheme and forecasting horizon), whereas, the total sentiment index, EUESI, and the Industry CI bring the best out-of-sample predictors when the Linear-LS model is estimated, irrespective of the benchmark model. Hence, our analysis reveals through the MIDAS estimations the vital role of the higher frequency Consumption Sentiment Indicator not only in-sample but also out-of-sample for the EU economic outlook prospects. Remarkably, the MIDAS models provide the highest gains

in terms of RMSFE vis-a-vis both benchmarks, $r_i < 1$, as well as the highest gains in terms of RMSFE vis-a-vis the Linear-LS model when the confidence predictor is either the Consumer or the Construction survey. All MIDAS models provide a statistically significant lower RMSFE compared to that of the Linear-LS model when the high-frequency predictor is the Consumer survey, while this holds true also when forecasting beyond one-quarter ahead and regardless of the benchmark model considered. On the other hand, the BMIDAS and PMIDAS models provide a lower RMSFE versus the corresponding Linear-LS model when the high-frequency predictor is the Building survey, but only when forecasting one-quarter ahead ($h = 1$). It is point mentioning that comparing the predictive accuracy between the traditional Linear-LS model (based on conventional aggregation techniques) and the mixed-sampling MIDAS models, it turns out that forecasts are more accurate using the latter model when the high-frequency predictor is the Consumption CI, according to the Diebold-Mariano test. Additionally, in unreported forecast evaluation implementations, the consumer survey was found to be a more accurate predictor than combining all sentiments together – which is essentially the total sentiment index (ESI) in the case where a MIDAS model is estimated. In the case of estimating the common-frequency model, oppositely, the total sentiment index (ESI) was found to be more accurate than its subset sentiment components. Lastly, when it comes to model comparison between the different mixed-frequency aggregation schemes, it seems that the BMIDAS and PMIDAS models with consumer survey as predictor outperform all the other MIDAS weighting schemes (as well as the parameter-free Linear-LS model) when forecasting both one-quarter and four-quarter ahead.

Momentously, for our analysis to be as robust as possible, the out-of-sample results were estimated also for the best-fitted models (in terms of the BIC criterion) over the period 1995Q1-2007Q4 which corresponds to the training sample period. Out-of-sample estimation results for the sub-period "best" models are similar to those found for the full-period "best" models. That is, MIDAS models provide the highest gains in terms of RMSFE vis-a-vis both benchmark models and thus the highest gains in terms of RMSFE vis-a-vis the Linear-LS model when the sentiment variable is EUCONS. In contrast, Linear LS models, provide the highest gains in terms of MSFE vis-a-vis both benchmark models and thus the highest gains in terms of MSFE vis-a-vis both MIDAS models when all other sentiment variables are considered. Overall, the strong predictive ability of the monthly-frequency Consumption survey in forecasting the quarterly EU GDP growth is robust even when the in-sample best-fitted models are evaluated for different sample periods. Similarly, in the recent study of Claveria (2021), the opinion of consumers and businesses regarding the expected developments of certain variables seem to substantially affect the economic forecasting procedure. Through machine learning techniques they show that consumer surveys provide forecasting gains compared to two alternative quantification procedures in projecting quarterly unemployment expectations for the euro area.

The answers to specific questions regarding the consumption sector seem to be an important requirement for the EU GDP growth prospects, especially when their higher sampling monthly frequency is exploited – as indicated by our analysis. The corresponding out-of-sample analysis using the consumptions' questions as predictors of the EU GDP growth are reported in Table 4. The questions include the financial situation over the last and next 12 months (EUCONS_q1 and EUCONS_q2), the general economic situation over the next 12 months (EUCONS_q4), and the major purchases over the next 12 months (EUCONS_q9). The ratio of RMSFEs for each Consumer Confidence Indicator (CCI) used in the models is computed as follows:

$$r_i = \frac{RMSFE_{predictive\ model,CCI_i}}{RMSFE_{benchmark\ model}}$$

where i represents the CCI used in the predictive model and $i = 1, \dots, 5$. When the ratio is lower than one, it means that the predictive model based on a given Consumption Confidence Indicator, i, outperforms the benchmark AR(p) or RW model and vice versa.

Table 4: Out-of-sample estimation results of the MIDAS regression models when low-frequency variable is quarterly EU GDP and high-frequency predictors are monthly Consumer Confidence Indicators (CCIs) vis-à-vis the corresponding common-frequency Linear-LS models.

Ratios of RMSFEs when the benchmark model is the RW										
	LINEAR		**BMIDAS**		**EMIDAS**		**PMIDAS**		**UMIDAS**	
	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$
EUCONS	**0.90**	0.90	**0.81****	**0.80****	**0.85***	**0.82***	**0.81****	**0.80****	**0.85***	**0.82***
EUCONS_q1	0.92	0.91	0.91	0.89	0.91	0.90	0.90	0.88	0.94	0.94
EUCONS_q2	0.94	0.93	0.95	0.89***	0.92**	0.89***	0.92**	0.89***	0.92**	0.89***
EUCONS_q4	0.92	0.90	0.86*	0.84*	0.89*	0.86*	0.85*	0.83*	0.89	0.86*
EUCONS_q9	0.92	**0.88**	0.88	0.86	0.93	0.85**	0.88	0.85	0.93	0.85**
Ratios of RMSFEs when the benchmark model is the AR(p)										
	LINEAR		**BMIDAS**		**EMIDAS**		**PMIDAS**		**UMIDAS**	
	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$
EUCONS	**0.91**	0.98	**0.82****	**0.87****	**0.85***	**0.89***	**0.82****	**0.86****	**0.86***	**0.89***
EUCONS_q1	0.92	0.98	0.92	0.97	0.92	0.97	0.91	0.95	0.95	1.01
EUCONS_q2	0.95	1.00	0.96	0.96***	0.93**	0.96***	0.93**	0.96***	0.93**	0.96***
EUCONS_q4	0.93	0.97	0.86*	0.91*	0.90*	0.93*	0.86*	0.90*	0.90	0.93*
EUCONS_q9	0.93	**0.96**	0.88	0.93	0.94	0.92**	0.88	0.92	0.94	0.92**

**: p-values of the Diebold-Mariano test*

From the out-of-sample estimation results it turns out that almost all models are capable to outperform both benchmark models (except the LINEAR and UMIDAS models with EUCONS_q2 and EUCONS_q1 as predictors, respectively, and the AR(p) model as benchmark). In almost all cases, the total Consumer Confidence Indicator (CCI) and its questions provide a ratio lower than one, $r_i < 1$, and thus are considered to be good out-of-sample predictors. Interestingly, the CCI brings the best out-of-sample one-quarter ahead ($h = 1$) predictor among all consumer sentiments in the table with the lowest RMSFE when both a mixed-frequency MIDAS model (regardless of the aggregation scheme) and a common-frequency Linear-LS model are estimated. Hence, incorporating the analysis of the Consumption survey's questions, it turns out that using the total CCI rather than a particular household question is more beneficial in terms of forecasting, independently of the mixed-frequency weighting function and the frequency considered. Notably, in the case of forecasting four-quarters ahead ($h = 4$), major purchases over the next 12 months gain importance through the common-frequency estimation. Outstandingly, the MIDAS models provide the highest gains in terms of RMSFE vis-a-vis both benchmarks, $r_i < 1$, as well as the highest gains in terms of RMSFE vis-a-vis the Linear-LS model when the confidence predictor is either the total CCI or its subset questions. All MIDAS models provide a lower RMSFE compared to that of the Linear-LS model when the high-frequency predictor is the total CCI, while the majority of the MIDAS weighting schemes provide a lower RMSFE versus the corresponding Linear-LS model when the high-frequency predictor is a specific consumer question. Likewise the findings of Table 3, comparing the predictive accuracy between the traditional Linear-LS model

and the MIDAS models, it turns out that forecasts are more accurate using the latter model when the high-frequency predictor is, especially, the total CCI, but also a particular household question, according to the Diebold-Mariano test. Furthermore, in unreported forecast evaluation implementations, the total CCI forecasts are better than forecasts based on consumption questions individually, regardless of the frequency considered in the models. Last but not least, when it comes to model comparison between both the different mixed-frequency aggregation schemes and the common-frequency model, it seems that the BMIDAS and PMIDAS models with the total CCI as predictor outperform all the other differently aggregated common- and mixed-frequency models. The results hold for both benchmark models considered in our analysis.

In conclusion, our empirical analysis using soft survey predictors indicates strong arguments in favor of the mixed-frequency models and the consumer survey in tracking and forecasting (short-term and long-term) the EU GDP growth. The MIDAS models produce a statistically significant higher estimated slope coefficient (i.e. existence of bias in the common-frequency model) and provide statistically significant forecasting gains against both the Linear-LS model and the traditional AR(p) and RW benchmark models. Most of all, the MIDAS models enhance the vital role of the consumer sentiment predictor in the EU economic outlook prospects amid the large and significant estimated coefficient of the CCI on the EU GDP growth, the relatively good fitness of the models (in terms of the BIC criterion), as well as the highly accurate out-of-sample performance (in terms of the RMSFEs) of the models when consumer survey is used as a predictor. Notably, the good in-sample and out-of-sample performance of the CCI is compared to all the sentiments composing the total ESI Index and the total Index itself, as well as the four household-assigned questions used to compute the total CCI Index. The question of whether consumer confidence has a strong economic impact has also been tried to be answered by Barsky and Sims (2012). Particularly, using an animal spirits-based Dynamic Stochastic General Equilibrium (DSGE) model, they showed that unexpected fluctuations in consumer confidence are prognostic of long-term fluctuations in key macroeconomic variables, where the comovements between consumer confidence and economic activity are mainly driven by fundamental news.

The relatively large impact of the Consumption sentiment on the EU GDP growth and its relatively good in-sample and out-of-sample performance through the MIDAS estimations constitute the sentiment indicator itself a valuable gauge for GDP movements. The importance of consumer sentiment has been extensively studied within the literature. For instance, Matsusaka and Sbordone (1995) showed, in the Granger causality sense, the significant added information in the US GDP forecasts when the Michigan consumption sentiment was added to their analysis. In the same way, Batchelor and Dua (1998) indicated the improvements in the US GDP forecasting exercises during the 1991 recession that could have been done under consideration of the Conference Board Consumption Confidence Index. More recently, Christiansen et al. (2014) assessed the role of the Michigan consumption sentiment and the Purchasing Managers Index (PMI) in forecasting the US recessions, showing through a probit model estimation that both sentiments are not only a strong predictor of future recessions on their own, but combining them with either classical recession predictors (e.g. term spread, short rate, and stock market index) or common factors (balanced panel of macroeconomic and financial time series) provides even stronger recession predictions. Their study, however, juxtaposes our findings since they found that the business sentiment is a substantially stronger predictor of recessions than the consumer sentiment. So far in our analysis, the Consumption CI provided by the European Commission, causes among the largest impacts on EU GDP growth, bringing the best-fitted model, while it brings also the best out-of-sample predictor in terms of forecasting errors compared to all the other sentiment variables. Notably, in our subsequent empirical analysis with financial data as

predictors, it will be also shown that the CCI not only brings the best out-of-sample predictor compared to the other sentiment predictors but also compared to common recession predictors including the euro area stock price index. Furthermore, Dees and Brinca (2013) showed through simple models and VAR analysis the existence of a significant link between consumer sentiment and household consumption in the US and the euro area economies, as well as that the shock in one country could pose declines in consumer confidence in various other countries and thus affect their economic outlooks.

Last but not least, the importance of the Consumption CI is also shown in the work of Jongrim and Inhwan (2021) where they inspected the global confidence cycles role – measured as the common factor across a wide assortment of business or consumer survey confidence indicators in global macroeconomic fluctuations during the period 1985-2019. Estimating a Factor-Augmented Vector Autoregression (FAVAR) model with a database including a set of 39 countries (25 advanced economies and 14 emerging market economies), they showed that global consumer confidence cycles have played a major role in global business cycle variations, reflecting more than a third of total variations. Outstandingly, they showed that while global business confidence shocks are inherently demand-driven, global consumer confidence shocks reflect not only demand but also supply shocks. Overall, our analysis is novel in terms of modelling compared to the existing literature, as it utilizes a mixed-frequency model and in particular the MIDAS model to show that furthermore to the neglected significant information, the poorer fitness, and the lower forecasting gains provided by the traditional common-frequency models, Consumer sentiment is a fundamental leading indicator for the European Union economic outlook prospects. At this point, it is considered appropriate to emphasize that there does not exist such a study that analyses the impact of soft survey and financial variables on the economic outlook for Europe in which there is a lot of heterogeneity across countries.

3.2.3. The role of Financial Indicators (FIs)

Our second objective is to explore the impact of the Financial Indicators (FI) in describing and anticipating movements in the EU GDP growth through both common and mixed frequency models and to compare their performance to the soft survey indicators. The in-sample estimation results of quarterly EU GDP models are reported in Table 5. This table demonstrates the estimation results of the Linear-LS regression model with common frequency variables (based on conventional aggregation techniques) versus the alternative MIDAS models with predictors sampled at a higher monthly frequency with the intention to reveal once more the *bias* incurred when a Linear-LS model is estimated instead of a MIDAS model. Correspondingly with the Confidence Indicators' analysis, in Table 5 are reported the estimated slope coefficient of the GDP growth, $\hat{\beta}_{GDP}$**,** the estimated slope coefficient of each FI, $\hat{\beta}_{FI}$, the BIC for each single-variable model, as well as the LM statistic. Like before, the estimated slope coefficient of each financial predictor in both the Linear-LS models and the NLS-MIDAS models with beta and exponential Almon weights is estimated within the regression. For the PMIDAS and UMIDAS models, the slope coefficient is computed as the sum of the estimated monthly lags of each FI where the significance of the slope coefficient is taken as the significance of the most important lag among the estimated polynomials and lags. Moreover, the models presented in the table are once again the best models according to information criteria; the augmentations of GDP growth that compose the estimated slope coefficient of GDP growth and the number of lags of each financial predictor that compose the estimated slope coefficient of the FI are such that provide the best-fitted models for each single-variable model.

Table 5: In-sample estimation results (1995Q1-2019Q4) of the MIDAS regression models when low-frequency variable is quarterly EU GDP and high-frequency predictors are monthly Financial Indicators (FIs) vis-à-vis the corresponding common-frequency Linear-LS models.

	Monthly Frequency of Financial Indicator (FI)							
	BMIDAS				**EMIDAS**			
	$\widehat{\beta}_{GDP}$	$\widehat{\beta}_{FI}$	**BIC**	**LM**	$\widehat{\beta}_{GDP}$	$\widehat{\beta}_{FI}$	**BIC**	**LM**
EASTOXX50	0.425***	0.228***	0.140	0.127	0.425***	0.240***	0.110	0.133
EASTOXX	0.408***	**0.255*** **	**0.113**	0.141	0.418***	**0.241*** **	**0.064**	**0.057**
GEGBY10Y	0.684***	-0.101*	0.302	0.430	0.673***	-0.105*	0.263	0.372
EURIBOR3	**0.994*** **	-0.237***	0.136	**0.010**	**0.991*** **	-0.195***	0.110	**0.009**
EURIBOR6	0.991***	-0.231***	0.121	**0.007**	0.855***	-0.151***	0.088	**0.072**
EURIBOR12	0.802***	-0.154***	0.160	0.313	0.815***	-0.137***	0.117	0.204
BRENT	0.596***	0.056	0.289	0.971	0.574***	0.106**	0.250	1.000
WTI	0.616***	-0.029	0.292	0.839	0.585***	0.081	0.269	1.000
FUTURES	0.603***	0.022	0.296	0.813	0.576***	0.084	0.275	1.000
GOLD	0.634***	0.105	0.273	**0.066**	0.628***	0.044	0.277	0.310
SILVER	0.615***	0.091	0.266	0.227	0.585***	0.139*	0.254	0.647
CORN	0.572***	-0.131*	0.200	0.928	0.589***	0.053*	0.266	1.000
WHEAT	0.603***	-0.102	0.261	**0.068**	0.594***	0.080	0.283	0.787
	PMIDAS				**UMIDAS**			
	$\widehat{\beta}_{GDP}$	$\widehat{\beta}_{FI}$	**BIC**	**LM**	$\widehat{\beta}_{GDP}$	$\widehat{\beta}_{FI}$	**BIC**	**LM**
EASTOXX50	0.445***	**0.196*** **	0.105	0.208	0.546***	0.094***	0.086	1.000
EASTOXX	0.439***	0.194***	**0.067**	0.142	0.526***	0.109***	**0.038**	1.000
GEGBY10Y	0.675***	-0.101	0.260	0.528	0.611***	0.010	0.207	1.000
EURIBOR3	0.846***	-0.144*	0.109	0.270	0.802***	-0.127***	0.089	0.512
EURIBOR6	**0.864*** **	-0.144**	0.085	0.139	**0.808*** **	**-0.131*** **	0.074	0.361
EURIBOR12	0.809***	-0.132**	0.115	0.329	0.765***	-0.114***	0.092	0.571
BRENT	0.614***	-0.020*	0.213	0.381	0.607***	0.057*	0.180	1.000
WTI	0.611***	-0.028*	0.231	0.524	0.604***	0.053	0.181	1.000
FUTURES	0.608***	-0.037	0.239	0.572	0.599***	0.038	0.195	1.000
GOLD	0.627***	-0.060	0.227	**0.067**	0.628***	0.044	0.184	0.126
SILVER	0.600***	-0.040	0.224	0.282	0.622***	0.030	0.198	1.000
CORN	0.635***	-0.030***	0.168	1.000	0.589***	0.053*	0.173	1.000
WHEAT	0.613***	-0.106	0.224	**0.102**	0.608***	0.014	0.205	1.000
	Quarterly Frequency of Financial Indicator (FI)							
	LINEAR							
	$\widehat{\beta}_{GDP}$	$\widehat{\beta}_{FI}$	**BIC**					
EASTOXX50	0.477***	0.102***	0.058					
EASTOXX	0.462***	0.111***	**0.029**					
GEGBY10Y	0.571***	0.045*	0.177					
EURIBOR3	**0.914*** **	**-0.139*** **	0.161					
EURIBOR6	0.896***	-0.133***	0.154					
EURIBOR12	0.848***	-0.116***	0.162					
BRENT	0.562***	0.072**	0.151					
WTI	0.567***	0.064**	0.161					
FUTURES	0.569***	0.061**	0.165					
GOLD	0.617***	0.009	0.208					
SILVER	0.590***	0.054**	0.170					

CORN	0.637***	-0.013***	0.111
WHEAT	0.599***	0.030	0.194

***, **, ***: significance at 10%, 5%, 1% (two-sided p-values)*

***LM Test**:= $T(SSR_0^{LS}\text{-}SSR_1^M)/SSR_0^{LS} \xrightarrow{d} \chi^2(r)$*

The following general conclusions can be inferred from Table 5. Contrarily to the in-sample empirical analysis with survey predictors, the total market Euro Stoxx Price Index (EASTOXX) brings the best-fitted model (in terms of the BIC criterion) irrespective of the frequency employed within the models. That is, the EASTOXX financial predictor brings the best-fitted model among all financial predictors when a MIDAS model is estimated, regardless of the MIDAS weighting scheme (with UMIDAS providing the lowest BIC value), while it also brings the best-fitted model among all financial predictors when a Linear-LS model is estimated. This finding reflects the strong impact of the total market Euro Stoxx Price Index in describing fluctuations in GDP growth. In comparison, however, to the empirical in-sample analysis with sentiment predictors where the MIDAS model with the consumer survey as a predictor provided a better-fitted model compared to the Linear-LS model with the ESI as a predictor, in the in-sample empirical analysis with financial predictors, the Linear-LS model with the EASTOXX financial predictor provides a better-fitted model compared to the corresponding MIDAS models. It can be therefore concluded through the comparison between the best-fitted models using common or mixed frequencies that, the total market Euro Stoxx Price Index can describe better the movements in the EU GDP growth within the common-frequency Linear-LS model rather than within the MIDAS models. Nevertheless, essential improvement can be achieved using the MIDAS models instead of the Linear-LS model when considering other FIs as predictors. In particular, the fitness of the model effectively improves when allowing for the higher frequency of the financial predictor rather than its low-quarterly frequency for all three Euribor interest rates, as well as for the prices of the gold precious metal. Analytically, the BIC value is 0.154 when the common-frequency model using the Euribor interest rate with a maturity of six months (EURIBOR6) as a predictor is estimated, whereas it is appraised to be much smaller when the corresponding MIDAS model is estimated; it is 0.121, 0.088, 0.085, and 0.074 when BMIDAS, EMIDAS, PMIDAS, and UMIDAS models are estimated, respectively. Similar results apply to the Euribor interest rates with a maturity of three and twelve months. Moreover, the BIC value is 0.208 when the Linear-LS model is estimated using the gold precious metal price as a predictor, while it is estimated to be 0.184 when a UMIDAS model is estimated. Observing the estimated slope coefficients of each FI, it seems that the Stock Price Indices and the Euribor interest rates cause the largest effect on the EU GDP growth, depending on the model being estimated. To be more precise, when the BMIDAS, EMIDAS, and PMIDAS models are estimated, either the total market Stock Price Index or the subset Euro Stoxx 50 Price Index causes the largest impact on EU GDP growth compared to all other financial predictors, while when the unrestricted common and mixed frequency models are estimated (Linear-LS and UMIDAS), the Euribor interest rates with a maturity of three and six months, respectively, cause the largest impact on EU GDP growth vis-à-vis all other financial predictors.

Estimation results indicate that bias is not an outlandish fact and incurs even when the explanatory variable is a Financial Indicator (FI). The temporal aggregation results show that the estimated slope coefficient of a particular FI can be considerably biased at low/quarterly frequency. MIDAS estimations produce statistically significant larger estimated slope coefficients of specific FIs than the corresponding traditional Linear-LS model, revealing the strongest effect of certain FIs on EU Real GDP growth, which is omitted when a Linear-LS regression model is estimated instead of a MIDAS model. For instance, the estimated slope coefficient of the

EURIBOR6 financial predictor in a Linear-LS model is equal to -0.133, whereas, it is much greater when estimated in a MIDAS model; it is appraised to be -0.231, -0.151, and -0.144 when BMIDAS, EMIDAS, and PMIDAS are estimated, respectively. The bias of the estimated slope coefficient when estimating the Linear-LS model rather than the corresponding MIDAS model, especially that with beta weights, is proved using the LM statistic (see Table 5). The estimations of the LM test show the existence of bias in the estimated slope coefficient for several other financial predictors in addition to the EURIBOR6 financial predictor. Bias as already known is linked to the well-known problem of an omitted variable in the regression model. The omitted variable here involves monthly data of the regressor which are demonstrated through a weighting scheme in a MIDAS model. Generally, bias depends on the correlation between the dependent variable and the regressor and the cumulative weighting scheme of the MIDAS regression, while amid the memory decay pattern, the cumulative weighting scheme is negative for most declining weights. It is worth pointing out that compared to the empirical analysis with survey predictors, not all Financial Indicators are statistically significant in all kinds of models, while the sign of the estimated FI might be either positive or negative, depending on the model being estimated.

On the whole, several valuable results can be recapitulated from our in-sample empirical analysis using financial data as predictors. Initially, MIDAS models show that there is important information coming from the financial indicators which is omitted when the common-frequency Linear-LS model is estimated instead of the corresponding mixed-frequency MIDAS model (bias). Secondly, the fitness of the models substantially improves using the MIDAS models versus the corresponding Linear-LS models for several indicators. Lastly, the total market Stock Price Index brings the best-fitted model regardless of the model estimated (frequency and aggregation scheme). In the subsequent stage, we move to our out-of-sample empirical analysis with financial indicators as predictors to evaluate their performance also out-of-sample and then compare it with the out-of-sample performance of the sentiment indicators as predictors.

3.2.4. Out-of-Sample Forecasting Performance of FIs

After the in-sample estimation analysis, the forecasting performance of Financial Indicators for the GDP growth in the EU is being studied. The training sample period is once again 1995Q1-2007Q4, and the evaluation sample periods are 2008Q1-2019Q4 and 2008Q4-2019Q4. The out-of-sample estimation results of quarterly EU GDP models when forecasting one-quarter ($h = 1$) and four-quarters ($h = 4$) ahead are reported in Table 6, which indicate the ratios of Root Mean Squared Forecasting Errors (RMSFEs) of EU GDP growth between the five types of predictive models (LINEAR, BMIDAS, EMIDAS, PMIDAS, and UMIDAS) and the AR(p) and RW benchmark models. The p-values testing the null hypothesis of equivalent predictive ability between the Linear-LS model and the MIDAS models based on the Diebold-Mariano test (2002) are also indicated in Table 6. It should be stated that as in the out-of-sample empirical analysis with survey confidence predictors, the out-of-sample results are once more with regards to the best-fitted models (in terms of the BIC) chosen in the previously in-sample discussed section. The ratio of RMSFEs for each Financial Indicator (FI) used in the models is computed as follows:

$$r_i = \frac{RMSFE_{predictive\ model,FI_i}}{RMSFE_{benchmark\ model}}$$

where i represents the FI used in the predictive model and i is each individual financial predictor or group-specific combination based on model averaging techniques. Correspondingly, when the ratio of RMSFEs is lower than one, it means that the predictive model based on a given Financial

Indicator or group-specific combination, i, outperforms the AR(p) or RW benchmark models and vice versa.

Forecast combinations of single predictors include simple mean, simple median, Least-squares, Mean square error, MSE ranks, smooth AIC weights, and SIC weights, where the averaging technique providing the lowest RMSFE ratio was chosen for all types of models each time. At this stage, forecast combinations of single financial predictors are preferred to forecasts based on individual financial predictors since they provide solutions to the potential model uncertainty problem that might occur when focusing on a single model (Andreou et. al (2013)). In Table 6 the group "Stocks" in both forecasting horizons refers to the total market Stock Price Index, bringing the best out-of-sample predictor between the two stock price indices for all kinds of models, except for the UMIDAS model where a forecast combination between the two types of regressors is preferred. The group "Euribors" mainly refers to combinations between the three Euribor rates when forecasting one-quarter ahead ($h = 1$), except for the EMIDAS model where the single EURIBOR3 financial predictor brings the best out-of-sample predictor among the three Euribor interest rates. In the case of forecasting four-quarters ahead ($h = 4$), the single EURIBOR3 financial predictor brings the best out-of-sample predictor among the three Euribor interest rates when the LINEAR and EMIDAS models are estimated and the single EURIBOR6 financial predictor when the BMIDAS model is estimated, while combinations between the three Euribor rates are considered when the PMIDAS and UMIDAS models are estimated. Finally, the group "Commodities" refers only to individual commodity prices for all kinds of models when forecasting both one-quarter and four-quarters ahead, as it turns outs that individual forecasts outperform forecasts based on combinations of all commodity predictors. Depending on the model being estimated, a different commodity price brings the best out-of-sample predictor among all commodity predictors. Notably, Table 6 reports also a group named "Sentiments". Following our empirical analysis with surveys as predictors, this group refers to the total sentiment predictor – the ESI in the case of the common-frequency Linear-LS model, whereas in the case of a MIDAS model, the group refers to the Consumption Confidence Indicator (CCI).

Table 6: Out-of-sample estimation results of the MIDAS regression models when low-frequency variable is quarterly EU GDP and high-frequency predictors are monthly financial and sentiment predictors/combinations vis-à-vis the corresponding common-frequency Linear-LS models.

Ratios of RMSFEs when the benchmark model is the RW										
	LINEAR		**BMIDAS**		**EMIDAS**		**PMIDAS**		**UMIDAS**	
	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$
Stocks	**0.85**	**0.82**	**0.83**	**0.82**	**0.83**	**0.82**	**0.85**	**0.83**	**0.90**	**0.84**
Euribors	0.96	0.83	0.95	0.83	0.96	0.83	0.97	0.90	0.96	0.89
Commodities	0.95	0.87	0.96	0.89	0.97	0.90	0.96	0.89	0.98	0.91
Sentiments	0.85	0.83	**0.81**	**0.80**	0.85	0.82	**0.81**	**0.80**	**0.85**	**0.82**
Ratios of RMSFEs when the benchmark model is the AR(p)										
	LINEAR		**BMIDAS**		**EMIDAS**		**PMIDAS**		**UMIDAS**	
	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$
Stocks	**0.86**	**0.89**	**0.84**	**0.88**	**0.84**	**0.89**	**0.86**	**0.90**	**0.91**	**0.91**
Euribors	0.97	0.90	0.96	0.90	0.97	0.90	0.98	0.97	0.97	0.96
Commodities	0.96	0.95	0.97	0.96	0.98	0.97	0.97	0.96	0.99	0.98
Sentiments	0.86	0.90	**0.82**	**0.87**	0.85	0.89	**0.82**	**0.86**	**0.86**	**0.89**

Forecast Combinations: *Simple mean, Simple median, Least-squares, Mean square error, MSE ranks, smooth AIC weights, and SIC weights.*

From the out-of-sample estimation results it can be clearly seen that all models (common and mixed frequency) are capable of outperforming both benchmark models. In all cases, the forecast combination groups “Stocks”, “Euribors”, “Commodities”, and “Sentiments” exhibit a ratio lower than one, $r_i < 1$, and thus are considered to be good out-of-sample combined predictors. When comparing the predictive ability between the financial groups, it turns out that the “Stocks” group and in particular the total market Stock Price Index brings the best out-of-sample predictor, both one-quarter and four-quarters ahead, with the lowest RMSFE ratio when estimating either the Linear-LS model or the MIDAS models. The computed ratios are lower compared to the models with other financial variables/groups as predictors, regardless of the benchmark model. The advantage of using financial variables as predictors in MIDAS models was also exploited by Andreou et. al (2013), where showed that MIDAS regression models using daily financial information via daily financial assets or factors outperform quarterly forecasts of U.S. real GDP growth beyond the quarterly macroeconomic factors. Their analysis, however, differs from our analysis in several ways as they did not provide a further analysis showing the great pros of using survey predictors, their analysis was conducted for the US and not for the EU, while the advantages of specific financial predictors such as the Stock Price Index are not provided.

When it comes to the appraisal between the common and mixed frequency models, it turns out that the MIDAS models provide the highest gains in terms of RMSFE ratios vis-a-vis both the benchmarks and the Linear-LS model, $r_i < 1$, when the financial group predictors are Stocks and Euribor rates. Analytically, in the short-term forecasting horizon ($h = 1$) the NLS- BMIDAS and EMIDAS models provide a lower RMSFE ratio compared to that of the Linear-LS model when the high-frequency financial group predictor is “Stocks”, while the BMIDAS model provides a lower RMSFE ratio versus the corresponding Linear-LS model when the high-frequency financial group predictor is “Euribors”. In the long-term forecasting horizon ($h = 4$), both the BMIDAS and EMIDAS models outperform the corresponding common-frequency models when considering either the “Stocks” or the “Euribors” financial group predictors. Nonetheless the lower RMSFE ratios provided by the particular MIDAS models, testing the predictive accuracy of the underlying models through the Diebold-Mariano test (2002), it turns out that there does not exist a statistically significant forecasting gain for those models. In contrast, the empirical analysis with survey predictors showed that not only did the MIDAS models reveal the significant out-of-sample role of Consumption sentiment in forecasting the EU GDP growth, but also that the MIDAS models with the CCI as a predictor provide statistically significant gains compared to the corresponding common-frequency model, based on the Diebold-Mariano test.

Substantially, when it comes to comparing the best out-of-sample financial predictors with the best out-of-sample confidence predictors, it turns out that both in the short-term and long-term forecasting horizons, the majority of the mixed-frequency MIDAS models are in favor of the Sentiment predictors, whereas the common-frequency LINEAR-LS model is in favor of the Financial Stock predictor. More precisely, BMIDAS, PMIDAS, and UMIDAS models provide lower RMSFE ratios when considering the best out-of-sample sentiment (CCI) predictor vis-à-vis the corresponding MIDAS models with the best-out-of-sample financial (Stock Price Index) predictor, whereas the Linear-LS model provides a lower ratio when considering the best-out-of-sample financial (Stock Price Index) predictor rather than the best out-of-sample sentiment (ESI) predictor. For instance, in short-term forecasting horizon ($h = 1$) the RMSFE ratio is 0.81 when estimating the BMIDAS model with the CCI as a predictor, while it is 0.83 when estimating the BMIDAS model with the total Stock Price Index as a predictor. Analogously, the RMSFE ratio when estimating the Linear-LS model with the Stock Price Index as a predictor is 0.85 (0.8485),

while it is slightly larger (0.8492) when estimating the Linear-LS model with the ESI as a predictor. The results hold under the employment of the RW benchmark model, while similar results apply both in the case of the AR(p) benchmark model and in the long-term forecasting horizon ($h = 4$). Finally, when it comes to model comparison between the different mixed-frequency aggregation schemes, it seems that the PMIDAS model with the CCI predictor outperforms all the other MIDAS weighting schemes, but also the Linear-LS model with the financial (Stock Price Index) predictor both in the short-term and in the long-term. For instance, 0.81 is lower than 0.85 with RW as a benchmark and 0.82 is lower than 0.86 with the AR(p) as a benchmark when $h = 1$. Our findings somehow juxtapose the findings found in the analysis of Ferrara and Marsilli (2013) where it is shown that through the estimation of MIDAS models, stock prices improve the accuracy of the EA GDP growth compared to the ESI predictor. Our analysis not only enhances the use of sentiment predictors through the MIDAS models but also shows that using the CCI rather than the total ESI index improves the forecast accuracy of the EU GDP growth.

Likewise the empirical analysis with survey predictors, the out-of-sample results with financial predictors were estimated also for the best-fitted models (in terms of the BIC criterion) over the period 1995Q1-2007Q4 which corresponds to the training sample period. Out-of-sample estimation results for the sub-period "best" models were again similar to those found for the full-period "best" models. Comparing the out-of-sample results of the best-fitted models selected when the sample period stops in 2019Q4 and in 2007Q4, the CCI brings once more the best out-of-sample predictor among all sentiment and financial predictors, regardless of the selected best-fitted model within different sample periods and its significance is primarily exploited through the estimation of the MIDAS models. To summarize, our empirical analysis of forecasting the EU GDP growth using survey and financial predictors reveals the existence of bias of the estimated slope coefficient, regardless of the type of regressor (CI of FI), when a Linear-LS model based on traditional aggregation techniques is estimated rather than a mixed-frequency MIDAS model that considers the time-series behaviour of the data. It can be undoubtedly stated that the estimation of the traditional common-frequency model neglects any information about the timing of innovations to the high-frequency monthly data, while the imposition of an equal weighting scheme leads to omitting substantial information. Out-of-sample advantages of the MIDAS models are also at the forefront as MIDAS models are found to exhibit the highest gains in terms of RMSFE vis-a-vis the benchmarks, and thus the highest gains in terms of MSFE vis-a-vis the Linear-LS model when the financial predictors are either Stocks or Euribor rates, or even when the predictors are Sentiment indicators, both in the short-term and in the long-term forecasting horizons. Furthermore, the principal role of the Consumer survey, both in-sample and out-of-sample, is uncovered through the estimation of the MIDAS mixed-frequency models. In particular, the MIDAS models depict that the Consumer survey causes among the largest impacts on EU GDP growth compared to all other sentiments (in terms of the estimated slope coefficient), it brings the best-fitted model (in terms of the BIC value) among all sentiments, while it brings the best out-of-sample predictor (in terms of the RMSFE ratios) compared to not only all the other sentiment predictors but also compared to all financial predictors employed in our analysis. Last but not least, our analysis portrays that the majority of the MIDAS models are in favor of the CCI, whereas the Linear-LS model is in favor of the Financial Stock predictor. Putting all together, the MIDAS models outperform the Linear-LS model and the best out-of-sample sentiment predictor (Consumption) outperforms the best out-of-sample financial predictor (Stock Price Index) both in the short-term and in the long-term. Next, a corresponding robustness section considering other economies (entirely and not entirely aligned with the EU) is provided.

4. Robustness Section

This section provides a robustness analysis, evaluating the estimation outcomes for the Spain (ES) and the United Kingdom (UK) economies incurred from the corresponding models analysed for the European Union (EU) in Section 3.

4.1. Empirical Models – The ES case

4.1.1. The role of Survey Confidence Indicators (CIs) in Spain

The five countries with the highest correlation during the period 1995Q1-2019Q4 with the EU in terms of their economic outlook are France, Italy, Germany, the Netherlands, and Spain. Hence, we chose to conduct a similar analysis with that of the EU for Spain (ES) – a country with a relatively high correlation with the EU, still not the highest, to assess whether Consumer sentiment is the key leading indicator for a country relatively close to the EU with regards to their economic performance, but not entirely the same. Note that, bias issues and forecasting gains are again part of the analysis providing a comprehensive comparison between the common and mixed frequency models. The in-sample estimation results of quarterly ES GDP models are reported in Table 7. This table indicates the estimation results of the Linear-LS regression model with common frequency survey variables (based on conventional aggregation techniques) vis-à-vis the alternative MIDAS models with survey predictors sampled at a higher monthly frequency with the intention to reveal the bias incurred when a Linear-LS model is estimated instead of a MIDAS model. In the table are reported the estimated slope coefficient of the GDP growth, $\hat{\beta}_{GDP}$, the estimated slope coefficient of each CI, $\hat{\beta}_{CI}$, the BIC for each single-variable model, and the LM statistic. As before, the models presented in the table are the optimal models with regard to the number of low- and high-frequency lags.

Table 7: In-sample estimation results (1995Q1-2019Q4) of the MIDAS regression models when low-frequency variable is quarterly ES GDP and high-frequency predictors are monthly Confidence Indicators (CIs) vis-à-vis the corresponding common-frequency Linear-LS models.

	Monthly Frequency of Confidence Indicator (CI)							
	BMIDAS				**EMIDAS**			
	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CI}}$	**BIC**	**LM**	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CI}}$	**BIC**	**LM**
ESCONS	**0.853*** **	0.191***	**-0.941**	**0.007**	0.839***	0.215***	**-1.006**	**0.001**
ESESI	0.797***	0.059	-0.781	1.000	0.791***	0.069**	-0.826	1.000
ESINDU	0.820***	0.035	-0.807	1.000	0.809***	0.065**	-0.834	1.000
ESSERV	0.817***	0.081	-0.809	**0.003**	0.822***	-0.049	-0.775	**0.089**
ESRETS	0.805***	**0.284*** **	-0.907	**0.016**	**0.861*** **	**0.367*** **	-0.875	**0.001**
ESBUILD	0.770***	0.204**	-0.789	0.241	0.769***	0.201**	-0.828	0.174
	PMIDAS				**UMIDAS**			
	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CI}}$	**BIC**	**LM**	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CI}}$	**BIC**	**LM**
ESCONS	**0.843*** **	0.211***	**-1.009**	**0.003**	**0.867*** **	**0.123*** **	**-0.990**	**0.020**
ESESI	0.796***	0.060	-0.828	1.000	0.816***	0.022	-0.886	1.000
ESINDU	0.835***	0.034***	-0.866	1.000	0.830***	0.037**	-0.913	1.000
ESSERV	0.824***	-0.002	-0.861	**0.003**	0.820***	-0.038**	-0.873	**0.030**
ESRETS	0.807***	**0.263**	-0.896	0.164	0.817***	0.035*	-0.906	1.000
ESBUILD	0.769***	0.202	-0.828	0.322	0.808***	0.024	-0.891	0.488

	Quarterly Frequency of Confidence Indicator (CI)		
	LINEAR		
	$\widehat{\beta}_{GDP}$	$\widehat{\beta}_{CI}$	BIC
ESCONS	**0.865*** **	0.073***	-0.956
ESESI	0.853***	**0.096*** **	**-0.960**
ESINDU	0.830***	0.082***	-0.943
ESSERV	0.815***	0.006	-0.825
ESRETS	0.828***	0.065***	-0.938
ESBUILD	0.802***	0.019	-0.886

***, **, ***: significance at 10%, 5%, 1% (two-sided p-values)*

***LM Test**:= T(SSR_0^{LS}-SSR_1^M)/SSR_0^{LS} $\xrightarrow{d}\chi^2(r)$*

Similarly with the EU analysis, essential improvement is achieved using the MIDAS models instead of the Linear-LS model. First, the fitness of the models effectively improves when allowing for the higher frequency of the survey predictor rather than its low- quarterly frequency. For instance, the BIC value is -0.956 when the common-frequency model using consumption survey as a predictor is estimated, whereas it is appraised to be much smaller when the corresponding MIDAS model is estimated; it is -1.006, -1.009, and -0.990 when EMIDAS, PMIDAS, and UMIDAS models are estimated, respectively. The fitness of the model effectively improves when exploiting the higher frequency data of also other soft survey predictors beyond the CCI. When the Services sentiment is used as a predictor, the fitness improves estimating either a PMIDAS or a UMIDAS model rather than the corresponding Linear-LS model. Similarly, when the Building CI is used as a predictor, the fitness improves estimating a UMIDAS model rather than the corresponding Linear-LS model. Secondly, when a MIDAS model is estimated the model using the CCI brings the best-fitted model in terms of the BIC criterion compared to all other models considering other sentiments as predictors (irrespective of the weighting function employed), while, the ESI brings the best-fitted model in terms of the BIC criterion compared to the models using other sentiment predictors when considering common sampling frequencies. For example, the estimated BIC value in the BMIDAS model considering the consumption survey as a predictor is -0.941, while considering other surveys as predictors such as the ESI, the estimated BIC value is larger (-0.781). Notably, even though the CCI might not cause the larger impact on the ES GDP growth, it still exhibits among the largest estimated slope coefficients among all other sentiments. Hence, combining the estimated slope coefficient and the estimated BIC, we can conclude that the CCI has a strong explanatory power on ES GDP growth. It should be mentioned that, compared to the in-sample analysis with EU survey predictors, there does not exist a robust pattern of the mixed-frequency models in terms of the BIC value; in general, the first three best-fitted mixed-frequency models are with Consumer, Retail, and Industry sentiments as predictors.

A point worth mentioning is the existence of bias in the estimated slope coefficient also for the ES case. MIDAS estimations produce statistically significant larger estimated slope coefficients of the Confidence Indicators than the corresponding traditional Linear-LS model revealing the significant information being neglected in the common-frequency model. For instance, the estimated slope coefficient of the CCI in the Linear-LS model is equal to 0.073, whereas, it is much greater when assessed in a MIDAS model; it is appraised to be 0.191, 0.215, 0.211, and 0.123 when BMIDAS, EMIDAS, PMIDAS, and UMIDAS models are assessed. The bias is proved using once again the LM test in Equation (2.8) employed by Andreou et. al (2010) to investigate bias issues. Remark that the estimations results of the LM statistic confirm that there is also

significant bias when not estimating the MIDAS models using either the Services or the Retail sentiment as a predictor and estimating the Linear-LS model instead. It is worth mentioning that, compared to the EU empirical analysis, not all ES sentiments provide statistical significance with respect to the ES GDP growth, while the sign of their impact on the ES GDP growth might be positive or negative, depending on the model being estimated (frequency and MIDAS aggregation scheme).

More than a few useful results can thus be synopsised from our ES in-sample empirical analysis using survey confidence indicators as predictors – similar to those obtained in the EU in-sample empirical analysis. At first, MIDAS models show that there is important information coming from the sentiment indicators which is marginalised when the common-frequency model is estimated instead of the corresponding mixed-frequency model (*bias*). Second, the fitness of several models substantially improves using the MIDAS models versus the corresponding Linear-LS models for several soft survey indicators. Last of all, the Consumption sentiment causes, even though not the greatest, among the greatest impacts on ES GDP growth versus all ES sentiment predictors, bringing the best-fitted model when a MIDAS model is estimated compared to the ESI predictor which brings the best-fitted model when a Linear-LS model is estimated compared to all other sentiment predictors. Next, the out-of-sample forecasting performance of the high-frequency ES survey predictors in projecting the low-frequency ES GDP growth is assessed.

4.1.2. Out-of-Sample Forecasting Performance of CIs in Spain

The out-of-sample forecasting performance of Confidence Indicators for the GDP growth in Spain (ES) is correspondingly evaluated, where the training sample period is 1995Q1-2007Q4 and the evaluation sample periods are 2008Q1-2019Q4 and 2008Q4-2019Q4. The related out-of-sample estimation results of quarterly ES GDP models when forecasting one-quarter ($h = 1$) and four-quarters ($h = 4$) ahead are reported in Table 8, which by the same token represent the ratios of Root Mean Squared Forecasting Errors (RMSFEs) of ES GDP growth between the five types of predictive models (LINEAR, BMIDAS, EMIDAS, PMIDAS, and UMIDAS) and the widely used in the literature AR(p) and RW benchmark models. The p-values testing the null hypothesis of equal predictive ability between the Linear-LS model and the MIDAS models based on the Diebold-Mariano test (2002) are over again reported in Table 8. The ratio of RMSFEs for each Confidence Indicator (CI) used in the models is computed, afresh, as follows:

$$r_i = \frac{RMSFE_{predictive\ model,CI_i}}{RMSFE_{benchmark\ model}}$$

where i represents the CI used in the predictive model and $i = 1, \dots, 6$. When the ratio is lower than one, it means that the predictive model based on a given CI, i, outperforms the benchmark AR(p) or RW model and vice versa.

Table 8: Out-of-sample estimation results of the MIDAS regression models when low-frequency variable is quarterly ES GDP and high-frequency predictors are monthly Confidence Indicators (CIs) vis-à-vis the corresponding common-frequency Linear-LS models.

Ratios of RMSFEs when the benchmark model is the RW										
	LINEAR		**BMIDAS**		**EMIDAS**		**PMIDAS**		**UMIDAS**	
	$h = 1$	$h = 4$	$h = 1$	$h = 4$	$h = 1$	$h = 4$	$h = 1$	$h = 4$	$h = 1$	$h = 4$
ESCONS	**0.94**	**0.85**	**0.90***	**0.84**	**0.91***	0.83*	**0.92**	**0.84**	**0.94**	**0.83*****
ESESI	0.96	0.87	0.96	0.93	1.00	0.95	0.96	0.93	1.00	0.95
ESINDU	0.96	0.86	0.97	0.94	1.00	0.95	0.99	0.95	1.00	0.95

ESSERV	1.02	0.96	1.02	0.98	1.02	0.97	1.01	0.97	1.01	0.96
ESRETS	0.99	0.96	0.98*	0.94***	0.97**	**0.81*** **	0.99	0.96	0.99*	0.94***
ESBUILD	0.99	0.95	0.96**	0.92**	0.97*	0.93*	0.96**	0.92*	0.98*	0.93**
Ratios of RMSFEs when the benchmark model is the AR(p)										
	LINEAR		**BMIDAS**		**EMIDAS**		**PMIDAS**		**UMIDAS**	
	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$
ESCONS	**0.94**	**0.89**	**0.90***	**0.88**	**0.91***	0.87*	**0.93**	**0.88**	**0.94**	**0.87*** **
ESESI	0.96	0.91	0.97	0.98	1.00	1.00	0.97	0.98	1.00	1.00
ESINDU	0.96	0.91	0.97	0.98	1.00	1.00	0.99	1.00	1.00	1.00
ESSERV	1.02	1.01	1.02	1.03	1.02	1.01	1.01	1.02	1.02	1.01
ESRETS	0.99	1.01	0.98*	0.99***	0.97**	**0.86*** **	0.99	1.00	0.99*	0.98***
ESBUILD	0.99	0.99	0.96**	0.97**	0.97*	0.98*	0.96**	0.97*	0.98*	0.98**

**: p-values of the Diebold-Mariano test*

The out-of-sample estimation results indicate that, like in the EU case, almost all models are capable to outperform both the RW and AR(p) benchmark models. Notably, consumer and building surveys provide always a ratio lower than one, $r_i < 1$, irrespective of the estimated model and the forecasting horizon ($h = 1$ or $h = 4$), and thereby in this manner they are considered to be good out-of-sample survey predictors. On the other hand, the other survey predictors might provide a ratio larger than one, $r_i > 1$, depending on the model being estimated and the forecasting horizon, while it is notable that the services survey predictor does not seem to provide a reliable out-of-sample predictor. Outstandingly, the CCI not only brings the best out-of-sample predictor among those in the table with the lowest RMSFE when a mixed-frequency MIDAS model is estimated (except the exponential aggregation scheme when $h = 4$) but also when the Linear-LS model based on traditional accumulation techniques is estimated. Furthermore, in unreported forecast evaluation exercises, the consumer survey was found to be a more accurate predictor in all kinds of models (except the EMIDAS model with $h = 4$ where the Retail sentiment seems to be a valuable predictor) than combining all sentiments together – which is essentially the total sentiment index (ESI). This finding juxtaposes, in part, the findings of the EU out-of-sample empirical analysis where the CCI was found to provide the lowest RMSFE ratios among all sentiments only in the case where a MIDAS model was estimated.

The EU findings might also be put adjacent to the ES findings as comparing the ratios of the MIDAS models with the corresponding ratio of the Linear-LS model when the predictor is the Consumer survey, the MIDAS models once more outperform both the benchmark models and the Linear-LS model. Importantly, the analysis for the Spanish economy shows that this finding holds also for the case where the predictor is either the Retail, the Building, or the Services survey predictor. Note that, according to the Diebold-Mariano test (2002), the MIDAS forecasting gains incorporating either Consumption, Retail, or Building sentiments as a predictor are statistically significant. Last of all, when it comes to one-quarter ahead ($h = 1$) model comparison between the different mixed-frequency aggregation schemes, it seems that the BMIDAS model with consumer survey as the predictor not only outperforms the Linear-LS model but also all the other MIDAS aggregation schemes. Interestingly, the four-quarters ahead ($h = 4$) model comparison shows that in addition to the Consumption survey predictor, the Retail sentiment brings a reliable out-of-sample predictor, outperforming the other MIDAS aggregation schemes and the common-frequency Linear-LS model.

Summarizing the results from the ES empirical analysis with ES survey confidence predictors, similar valuable results to that of the EU empirical analysis can be concluded. More specifically,

the MIDAS models once again indicate that there might occur bias of the estimated slope coefficient when a Linear-LS model is estimated rather than a corresponding mixed-frequency model, while the forecasting gains of the model based on different frequencies are statistically significant. It cannot be neglected from the outcomes the strong in-sample and out-of-sample role of the Consumer survey confidence on the GDP growth for the Spain economy. This is confirmed by the findings that the MIDAS models show the relatively large impact of the ES consumer survey on the ES GDP growth in combination with the relatively good fitness of the mixed-frequency models considering the CCI as a predictor compared to other predictors. Importantly, the out-of-sample good performance of the consumer survey is acknowledged when estimating both common and mixed-frequency models, while the performance of the MIDAS models based on the CCI predictor statistically significantly outperforms the corresponding of the common-frequency Linear-LS model. The valuable consumer confidence for several countries, including Spain, was recognized also by Eggers, Ellison, and Lee (2021) where they showed using a Regression Discontinuity Design (RDD) that a recession might lead to significant fluctuations of GDP growth triggered initially by discontinuous declines of the consumer confidence and thereby consumption growth. Next, the corresponding ES empirical analysis with financial indicators as predictors is provided.

4.1.3. The role of Financial Indicators (FIs) in Spain

Similarly with the EU empirical analysis, our second objective is to explore the impact of the Financial Indicators (FI) in describing and anticipating movements in the ES GDP growth through both common and mixed frequency models and once again to compare their performance to the soft ES survey indicators. The in-sample estimation results of quarterly ES GDP models with financial predictors are reported in Table 9. This table demonstrates the estimation results of the Linear-LS regression model with common frequency financial variables (based on conventional aggregation techniques) versus the alternative MIDAS models with financial predictors sampled at a higher monthly frequency with the intention to reveal once more the *bias* incurred when a Linear-LS model is estimated instead of a MIDAS model. Correspondingly with the Confidence Indicators' analysis, in Table 9 are reported the estimated slope coefficient of the GDP growth, $\hat{\beta}_{GDP}$**,** the estimated slope coefficient of each FI, $\hat{\beta}_{FI}$, the BIC for each single-variable model, as well as the LM statistic, while the models presented in the table are the best-fitted models (BIC).

Table 9: In-sample estimation results (1995Q1-2019Q4) of the MIDAS regression models when low-frequency variable is quarterly ES GDP and high-frequency predictors are monthly Financial Indicators (FIs) vis-à-vis the corresponding common-frequency Linear-LS models.

	Monthly Frequency of Financial Indicator (FI)							
	BMIDAS				**EMIDAS**			
	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{FI}}$	**BIC**	**LM**	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{FI}}$	**BIC**	**LM**
EASTOXX50	0.819***	0.018	-0.901	**0.012**	0.773***	0.062***	-0.867	0.169
EASTOXX	0.820***	0.021	-0.928	**0.005**	0.769***	0.063***	-0.877	0.154
GEGBY10Y	0.856***	-0.061	-0.794	0.384	0.844***	-0.079**	-0.832	0.654
EURIBOR3	**0.986*** **	-0.096***	-1.121	**0.000**	**1.002*** **	**-0.112*** **	-1.114	**0.000**
EURIBOR6	0.958***	-0.085***	**-1.136**	**0.000**	0.994***	**-0.112*** **	**-1.140**	**0.000**
EURIBOR12	0.945***	-0.088***	-1.114	**0.000**	0.940***	-0.099***	-1.136	**0.000**
BRENT	0.842***	-0.097*	-0.914	0.825	0.824***	0.071**	-0.851	1.000
WTI	0.850***	-0.068	-0.853	1.000	0.810***	0.033*	-0.808	1.000
FUTURES	0.845***	-0.074	-0.845	1.000	0.808***	0.018	-0.785	1.000

GOLD	0.806***	**-0.105***	-0.866	**0.006**	0.834***	0.030*	-0.811	0.218
SILVER	0.820***	0.007	-0.846	**0.048**	0.810***	0.038	-0.790	1.000
CORN	0.839***	-0.072***	-0.981	0.662	0.796***	0.022	-0.794	1.000
WHEAT	0.848***	-0.072	-0.852	**0.020**	0.814***	0.051**	-0.817	0.331
	PMIDAS				**UMIDAS**			
	$\widehat{\beta}_{GDP}$	$\widehat{\beta}_{FI}$	**BIC**	**LM**	$\widehat{\beta}_{GDP}$	$\widehat{\beta}_{FI}$	**BIC**	**LM**
EASTOXX50	0.814***	0.021*	-0.937	**0.018**	0.773***	0.062**	-0.914	0.169
EASTOXX	0.818***	0.023*	-0.970	**0.006**	0.785***	0.038**	-0.931	1.000
GEGBY10Y	0.854***	-0.061	-0.838	0.451	0.819***	-0.008	-0.873	1.000
EURIBOR3	**0.950*** **	-0.083***	-1.152	**0.000**	**1.002*** **	**-0.112*** **	-1.114	**0.000**
EURIBOR6	**0.950*** **	-0.085**	**-1.156**	**0.000**	0.955***	-0.103***	**-1.149**	**0.000**
EURIBOR12	0.940***	-0.099**	-1.136	**0.000**	0.909***	-0.090***	-1.147	**0.000**
BRENT	0.846***	-0.088***	-0.970	0.621	0.818***	0.049***	-0.935	1.000
WTI	0.846***	-0.086***	-0.898	1.000	0.810***	0.033*	-0.902	1.000
FUTURES	0.846***	-0.064***	-0.886	1.000	0.808***	0.018	-0.878	1.000
GOLD	0.798***	-0.104	-0.900	**0.010**	0.834***	0.030*	-0.904	**0.081**
SILVER	0.822***	**-0.113****	-0.885	**0.066**	0.825***	0.016	-0.878	1.000
CORN	0.833***	-0.071	-1.023	0.777	0.856***	-0.057***	-0.898	1.000
WHEAT	0.814***	-0.090	-0.893	**0.025**	0.816***	0.013	-0.878	1.000
	Quarterly Frequency of Financial Indicator (FI)							
	LINEAR							
	$\widehat{\beta}_{GDP}$	$\widehat{\beta}_{FI}$	**BIC**					
EASTOXX50	0.764***	0.036**	-0.925					
EASTOXX	0.761***	0.038***	-0.932					
GEGBY10Y	0.839***	-0.032**	-0.870					
EURIBOR3	0.927***	-0.058***	-1.007					
EURIBOR6	**0.935*** **	**-0.060*** **	-1.018					
EURIBOR12	0.921***	-0.056***	-0.993					
BRENT	0.843***	-0.022***	-0.998					
WTI	0.840***	-0.027***	-0.950					
FUTURES	0.840***	-0.029***	-0.941					
GOLD	0.820***	0.009	-0.873					
SILVER	0.811***	0.029*	-0.904					
CORN	0.845***	-0.025***	**-1.059**					
WHEAT	0.813***	0.020	-0.889					

, **, ***: significance at 10%, 5%, 1% (two-sided p-values)

***LM Test*:=** $T(SSR_0^{LS}\text{-}SSR_1^M)/SSR_0^{LS} \xrightarrow{d} \chi^2(r)$

The following general conclusions can be inferred from Table 9. Contrarily to the EU in-sample empirical analysis with financial predictors where the total market Euro Stoxx Price Index (EASTOXX) brought the best-fitted model (BIC) irrespective of the frequency employed within the models, the ES analysis shows that the Euribor interest rate with a maturity of six months (EURIBOR6) financial predictor brings the best-fitted model (BIC) in all MIDAS models, whereas the corn price brings the best-fitted model when a LINEAR-LS model is estimated. Comparing the best-fitted MIDAS models with the best-fitted Linear-LS model, it turns out that the MIDAS models provide a lower BIC value compared to the common-frequency model. For example, the BIC value when estimating the Linear-LS model with the corn oil price as a predictor is -1.059, while it is -1.156 when a PMIDAS model with the EURIBOR6 financial rate as a predictor is estimated. A

similar conclusion to that of the EU empirical analysis can be achieved; essential improvements can be attained using the MIDAS models instead of the Linear-LS model with FIs as predictors. In particular, the fitness of the model effectively improves when allowing for the higher frequency of a specific financial predictor rather than its low- quarterly frequency, including both Stock Price Indices, the Germany government bond yield, all three Euribor interest rates, the prices of the gold precious metal, as well as the wheat prices. For instance, the BIC value is -1.018 when the common-frequency model using the Euribor interest rate with a maturity of six months (EURIBOR6) as a predictor is estimated, whereas it is appraised to be much smaller when the corresponding MIDAS model is estimated; it is -1.136, -1.140, -1.156, and -1.149 when BMIDAS, EMIDAS, PMIDAS, and UMIDAS models are estimated, respectively.

Significantly, bias is not a bizarre fact in the ES case as well. Like in the EU case, MIDAS estimations produce statistically significant larger estimated slope coefficients of specific FIs than the corresponding traditional Linear-LS model, revealing the strongest effect of certain FIs on the ES GDP growth, which is omitted when a Linear-LS regression model is estimated instead of the MIDAS model. For instance, the estimated slope coefficient of the EURIBOR6 financial predictor in a Linear-LS model is equal to -0.060, whereas, it is much greater when estimated in a MIDAS model; it is appraised to be -0.085, -0.112, -0.085, and -0.103 when BMIDAS, EMIDAS, PMIDAS, and UMIDAS models are estimated, respectively. The bias in the estimated slope coefficient of not only the EURIBOR6 financial predictor but also of other soft financial predictors when estimating the Linear-LS model rather than the corresponding MIDAS model is proved using the LM statistic (see Table 9). Note that, likewise the EU case, not all Financial Indicators are statistically significant in all kinds of models and the sign of the estimated FI might be either positive or negative, depending on the model being estimated. The corresponding ES out-of-sample empirical analysis with financial predictors is provided in the next subsection.

4.1.4. Out-of-Sample Forecasting Performance of FIs in Spain

The corresponding out-of-sample estimation results of quarterly ES GDP models with financial predictors when forecasting one-quarter ($h = 1$) and four-quarters ($h = 4$) ahead are reported in Table 10. Once again, the ratio of RMSFEs for each Financial Indicator (FI) used in the models is computed as follows:

$$r_i = \frac{RMSFE_{predictive\ model,FI_i}}{RMSFE_{benchmark\ model}}$$

where i represents the FI used in the predictive model and i is each individual financial predictor or group-specific combination based on model averaging techniques. Correspondingly, when the ratio of RMSFEs is lower than one, it means that the predictive model based on a given Financial Indicator or group-specific combination, i, outperforms the AR(p) or RW benchmark models and vice versa. In Table 10 the group “Stocks” refers mainly to combinations between the two Stock Price Indices, except for the PMIDAS model where either the subset Euro Stoxx 50 Price Index or the total Stock Price Index is preferred, according to the forecasting horizon. The group “Euribors” mainly refers to the Euribor interest rate with a maturity of 12 months, except for the Linear-LS model where the rate with maturity of three months is preferred when forecasting one-quarter ahead ($h = 1$), while the corresponding three-month euribor interest rate is preferred in all kinds of models when forecasting four-quarters ahead ($h = 4$). Interestingly, the group “Commodities” refers only to the individual corn oil price for all types of models and for both forecasting horizons, except the Linear model with $h = 4$ where the West Texas Intermediate

(WTI) individual oil price is preferred. Lastly, recalling our ES out-of-sample empirical analysis with survey predictors, the group "Sentiments" refers only to the CCI for all types of models and forecasting horizons, except for the case where $h = 4$ and an EMIDAS model is being estimated where the Retail sentiment provides a valuable out-of-sample predictor.

Table 10: Out-of-sample estimation results of the MIDAS regression models when low-frequency variable is quarterly ES GDP and high-frequency predictors are monthly financial and sentiment predictors/combinations vis-à-vis the corresponding common-frequency Linear-LS models.

Ratios of RMSFEs when the benchmark model is the RW										
	LINEAR		**BMIDAS**		**EMIDAS**		**PMIDAS**		**UMIDAS**	
	$\boldsymbol{h=1}$	$\boldsymbol{h=4}$	$\boldsymbol{h=1}$	$\boldsymbol{h=4}$	$\boldsymbol{h=1}$	$\boldsymbol{h=4}$	$\boldsymbol{h=1}$	$\boldsymbol{h=4}$	$\boldsymbol{h=1}$	$\boldsymbol{h=4}$
Stocks	**0.92**	**0.89**	**0.97**	0.92	**0.96**	**0.92**	0.96	0.93	**0.96**	0.93
Euribors	0.99	0.95	0.99	**0.92**	1.00	0.92	0.99	0.95	0.99	**0.92**
Commodities	0.98	0.94	0.97	0.93	0.98	0.93	**0.96**	**0.92**	0.96	0.92
Sentiments	0.94	**0.85**	**0.90**	**0.84**	**0.91**	**0.81**	**0.92**	**0.84**	**0.94**	**0.83**
Ratios of RMSFEs when the benchmark model is the AR(p)										
	LINEAR		**BMIDAS**		**EMIDAS**		**PMIDAS**		**UMIDAS**	
	$\boldsymbol{h=1}$	$\boldsymbol{h=4}$	$\boldsymbol{h=1}$	$\boldsymbol{h=4}$	$\boldsymbol{h=1}$	$\boldsymbol{h=4}$	$\boldsymbol{h=1}$	$\boldsymbol{h=4}$	$\boldsymbol{h=1}$	$\boldsymbol{h=4}$
Stocks	**0.92**	**0.94**	**0.97**	0.97	**0.96**	**0.97**	0.96	0.97	**0.96**	0.97
Euribors	0.99	1.00	0.99	**0.97**	1.00	0.97	0.99	1.00	1.00	**0.96**
Commodities	0.98	0.98	0.98	0.98	0.98	0.97	**0.96**	**0.97**	0.96	0.96
Sentiments	0.94	**0.89**	**0.90**	**0.88**	**0.91**	**0.86**	**0.93**	**0.88**	**0.94**	**0.87**

Forecast Combinations: *Simple mean, Simple median, Least-squares, Mean square error, MSE ranks, smooth AIC weights, and SIC weights.*

Similarly with the EU case, the out-of-sample estimation results show that all models (both common and mixed frequency) are capable of outperforming both benchmark models. In all cases, the forecast combination groups "Stocks", "Euribors", "Commodities", and "Sentiments" exhibit a ratio lower or in some case equal to one, $r_i \leq 1$, and thus are considered to be good out-of-sample combined predictors. When comparing the one-quarter ahead ($h = 1$) predictive ability between the financial groups, it turns out that the "Stocks" group – a combination between the two Stock Price Indices brings the best out-of-sample predictor with the lowest RMSFE ratio when both a Linear-LS model and a MIDAS model are estimated, except for the PMIDAS model where the corn oil price brings the best out-of-sample predictor among all other financial predictors. The computed ratios are lower compared to the models with other financial variables/groups as predictors, regardless of the benchmark model. On the other hand, when comparing the four-quarters ahead ($h = 4$) predictive ability between the financial groups, different group predictors domain according to the model being estimated. That is, the "Stocks" group – a combination between the two Stock Price Indices brings the best out-of-sample predictor when either the Linear-LS model or the EMIDAS models are being estimated, while the three-month euribor interest rate provides the lowest ratio among the financial predictors in the case where the BMIDAS and UMIDAS models are being estimated. Likewise the one-quarter ahead forecasting exercise, the corn oil price brings the best out-of-sample predictor among all other financial predictors when a PMIDAS model is being estimated.

When it comes to the appraisal between the common and mixed frequency models, it turns out that the MIDAS models provide the highest gains in terms of RMSFE ratios vis-a-vis both the

benchmarks and the Linear-LS model when the financial group predictors are Euribor rates and Commodity prices, while, this was the case for the EU analysis when financial groups/predictors were Stocks and Euribor rates. In particular, in the case of forecasting one-quarter ahead ($h = 1$), the BMIDAS and PMIDAS models provide a lower RMSFE ratio compared to that of the Linear-LS model when the high-frequency financial group predictor is "Euribors", while the BMIDAS, PMIDAS, and UMIDAS models provide a lower RMSFE ratio versus the corresponding Linear-LS model when the high-frequency financial group predictor is "Commodities". Interestingly, when it comes to forecasting four-quarters ahead ($h = 4$), MIDAS models outperform the corresponding common-frequency model when considering either the "Euribors" or "Commodities" financial group, irrespective of the MIDAS aggregation scheme applied.

Considerably, when it comes to comparing the best out-of-sample financial predictors with the best out-of-sample confidence predictors, it turns out that all the mixed-frequency MIDAS models (not only a majority of them like in the EU case) are in favor of the Sentiment predictors. In the case of estimating the traditional common-frequency model, however, the Financial Stock predictor (likewise the EU case) is preferred for $h = 1$, while the Sentiment type predictor is preferred for $h = 4$. More precisely for $h = 1$, BMIDAS, EMIDAS, PMIDAS, and UMIDAS models provide lower RMSFE ratios when considering the best out-of-sample sentiment (CCI) predictor vis-à-vis the corresponding MIDAS models with the best-out-of-sample financial (Stock Price Index) predictor, whereas the Linear-LS model provides a lower ratio when considering the best-out-of-sample financial (Stock Price Index) predictor rather than the best out-of-sample sentiment (CCI) predictor. For instance, the RMSFE ratio is 0.90 when estimating the BMIDAS model with the CCI as a predictor, while it is 0.97 when estimating the BMIDAS model with the total Stock Price Index as a predictor. Analogously, the RMSFE ratio when estimating the Linear-LS model with the Stock Price Index as a predictor is 0.92, while it is 0.94 when estimating the Linear-LS model with the CCI as a predictor. The results hold under the employment of the RW benchmark model, while similar results apply in the case of the AR(p) benchmark model. Similar results can be obtained for $h = 4$, indicating the advantages of using the high-frequency monthly sentiment predictors vis-à-vis the high-frequency monthly financial predictors. Finally, when it comes to the one-quarter ahead ($h = 1$) model comparison between the different mixed-frequency aggregation schemes, it seems that the BMIDAS model with the CCI predictor (PMIDAS in the EU case) outperforms all the other MIDAS weighting schemes, but also the Linear-LS model with the financial (Stock Price Index) predictor; 0.90 is lower than 0.92 with either the RW or the AR(p) as a benchmark model. Interestingly, the four-quarters ahead ($h = 4$) model comparison shows that the PMIDAS model with the Retail sentiment predictor outperforms all the other MIDAS weighting schemes in addition to the Linear-LS model considering the CCI predictor, while once more all the other MIDAS weighting schemes that consider the CCI as predictor outperform the corresponding common-frequency model.

To recapitulate, our empirical analysis of forecasting the ES GDP growth using survey and financial predictors reveals the existence of bias of the estimated slope coefficient, regardless of the type of regressor, when a Linear-LS model based on traditional aggregation techniques is estimated rather than a mixed-frequency MIDAS model that considers the time-series behaviour of the data (a finding also of the EU empirical analysis). Out-of-sample advantages of the MIDAS models are also at the forefront since MIDAS models are found to exhibit the highest gains in terms of RMSFE vis-a-vis the benchmarks, and thus the highest gains in terms of MSFE vis-a-vis the Linear-LS model when the financial predictors are either Euribor rates or Commodity prices (Stock prices and Euribor interest rates in the EU case), as well as when predictors are Sentiment

indicators (in terms of best predictors/combinations). Additionally, the principal role of the Consumer survey, both in-sample and out-of-sample, is depicted through the MIDAS estimations. In particular, the MIDAS models portray that the Consumer survey causes among the largest impacts on ES GDP growth compared to all other sentiments (in terms of the estimated slope coefficient), brings the best-fitted model (in terms of the BIC value) among all sentiments, while it might bring the best out-of-sample predictor (in terms of the RMSFE ratios) compared to not only the sentiment predictors but also compared to all financial predictors employed in our analysis – an EU finding as well. Last but not least, our one-quarter ahead ($h = 1$) forecasting analysis displays that all the MIDAS models are in favor of the Sentiment Consumption predictor, whereas the Linear-LS model is in favor of the Financial Stock predictor. Putting all together, the MIDAS models outperform the Linear-LS model and the best out-of-sample sentiment predictor (Consumption) outperforms the best out-of-sample financial predictor (Stock Price Index) – an EU outcome too. Remarkably, the four-quarter ahead ($h = 4$) forecasting analysis, shows the preference of all kinds of models in favor of the sentiment compared to the financial predictors, while all the MIDAS models employing the CCI sentiment predictor or the MIDAS model based on exponential weights considering the Retail out-of-sample sentiment predictor beat the corresponding Linear-LS model.

4.2. Empirical Models – The UK case

4.2.1. The role of Survey Confidence Indicators (CIs) in the United Kingdom

In addition to Spain, we wanted to further extend our analysis by considering a country that does not belong to the five countries with the highest correlations with the EU (in terms of the GDP growth), a country that is among the largest national economies in the world, and that has been in the forefront lately amid the recent Brexit case. Bias issues and forecasting gains consist once again part of the analysis providing a comprehensive comparison between the common and mixed frequency models. The analogous in-sample estimation results of quarterly UK GDP models with survey predictors, following the same form as before, are reported in Table 11.

Table 11: In-sample estimation results (1995Q1-2019Q4) of the MIDAS regression models when low-frequency variable is quarterly UK GDP and high-frequency predictors are monthly Confidence Indicators (CIs) vis-à-vis the corresponding common-frequency Linear-LS models.

	Monthly Frequency of Confidence Indicator (CI)							
	BMIDAS				**EMIDAS**			
	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CI}}$	**BIC**	**LM**	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CI}}$	**BIC**	**LM**
UKCONS	0.561***	**0.207*** **	**-0.559**	0.513	0.560***	0.207***	**-0.603**	0.351
UKESI	0.520***	0.118**	-0.488	0.151	0.523***	0.137***	-0.494	0.499
UKINDU	**0.617*** **	-0.002	-0.478	**0.079**	0.568***	0.095**	-0.479	0.280
UKSERV	0.591***	0.086	-0.507	**0.035**	**0.599*** **	0.108	-0.488	0.186
UKRETS	0.611***	0.081*	-0.454	0.600	0.588***	0.155*	-0.483	0.919
UKBUILD	0.531***	0.152	-0.503	1.000	0.470***	**0.221*** **	-0.528	1.000
	PMIDAS				**UMIDAS**			
	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CI}}$	**BIC**	**LM**	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CI}}$	**BIC**	**LM**
UKCONS	0.560***	0.208	**-0.603**	0.551	0.624***	0.019	-0.528	1.000
UKESI	0.592***	0.076	-0.522	0.246	0.595***	**0.037***	-0.554	1.000
UKINDU	0.600***	0.028	-0.518	**0.099**	0.611***	0.031*	-0.547	0.776

UKSERV	**0.612*** **	0.102	-0.512	0.229	**0.644*** **	0.018	**-0.568**	1.000
UKRETS	0.604***	0.082	-0.490	0.837	0.628***	0.026	-0.544	1.000
UKBUILD	0.467***	**0.250*** **	-0.543	1.000	0.638***	0.008	-0.521	1.000

	Quarterly Frequency of Confidence Indicator (CI)		
	LINEAR		
	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{CI}}$	**BIC**
UKCONS	0.549***	0.098***	**-0.628**
UKESI	0.569***	0.052**	-0.572
UKINDU	0.597***	0.033	-0.546
UKSERV	**0.625*** **	0.035	-0.581
UKRETS	0.619***	0.040**	-0.573
UKBUILD	0.425***	**0.136*** **	-0.625

***, **, ***: significance at 10%, 5%, 1% (two-sided p-values)*

***LM Test*:=** $T(SSR_0^{LS}\text{-}SSR_1^M)/SSR_0^{LS} \xrightarrow{d} \chi^2(r)$

The UK in-sample empirical analysis with survey predictors seems to be disobedient to the empirical findings for the EU and ES economies. More specifically, essential improvement is not achieved using the MIDAS models instead of the Linear-LS model since the fitness of the models does not improve when allowing for the higher frequency of the survey predictor rather than its low- quarterly frequency. For instance, the BIC value is -0.628 when the common-frequency model using consumption survey as a predictor is estimated, whereas it is appraised to be larger when the corresponding MIDAS model is estimated; it is -0.559, -0.603, and -0.528 when BMIDAS, E/PMIDAS, and UMIDAS models are estimated, respectively. The only case where the fitness of the model slightly improves when exploiting the higher frequency data is when the survey predictor is the Industry CI in the UMIDAS model. Importantly, even though the CCI brings the best-fitted model among all survey predictors (irrespective of the model being estimated) proving its strong in-sample power also on the UK GDP growth, it seems that movements in the consumer survey are stronger within the common-frequency model rather than the mixed-frequency models for the UK GDP growth. It should be mentioned that likewise the ES analysis and in contrast to the EU analysis, there does not exist a robust pattern of the mixed-frequency models in terms of the BIC value, not all UK sentiments provide statistical significance with respect to the UK GDP growth, while the sign of their impact on the UK GDP growth might be positive or negative, depending on the model being estimated (frequency and MIDAS aggregation scheme). Lastly, bias seems to not be a big issue as in the EU and ES cases; the LM test provides a slight significance for some survey indicators in the BMIDAS and PMIDAS models only.

4.2.2. Out-of-Sample Forecasting Performance of CIs in the United Kingdom

The out-of-sample forecasting performance of Confidence Indicators for the GDP growth in the United Kingdom (UK) when forecasting one-quarter ($h = 1$) and four-quarters ($h = 4$) ahead is correspondingly evaluated, where the training sample period is once again 1995Q1-2007Q4 and the evaluation sample periods are 2008Q1-2019Q4 and 2008Q4-2019Q4. The corresponding out-of-sample estimation results of quarterly UK GDP models are reported in Table 12, where the ratio of RMSFEs for each Confidence Indicator (CI) used in the models is computed, afresh, as follows:

$$r_i = \frac{RMSFE_{predictive\ model,CI_i}}{RMSFE_{benchmark\ model}}$$

where i represents the CI used in the predictive model and $i = 1, \dots, 6$. When the ratio is lower than one, it means that the predictive model based on a given CI, i, outperforms the benchmark AR(p) or RW model and vice versa.

Table 12: Out-of-sample estimation results of the MIDAS regression models when low-frequency variable is quarterly UK GDP and high-frequency predictors are monthly Confidence Indicators (CIs) vis-à-vis the corresponding common-frequency Linear-LS models.

Ratios of RMSFEs when the benchmark model is the RW										
	LINEAR		**BMIDAS**		**EMIDAS**		**PMIDAS**		**UMIDAS**	
	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$
UKCONS	0.95	0.82	0.97	0.84	0.96	**0.82**	0.96	0.82	0.96	**0.82**
UKESI	0.96	0.82	0.94	0.81	0.96	0.83	1.00	0.87	0.96	0.83
UKINDU	0.94	0.81	0.94	0.85	**0.95**	0.83	0.95	**0.82**	**0.95**	0.83
UKSERV	1.05	0.91	1.01**	0.86*	1.03*	0.90	1.02*	0.86*	1.01***	0.86***
UKRETS	0.98	0.83	1.04	0.85	1.01	0.86	1.05	0.87	1.01	0.86
UKBUILD	**0.86**	**0.79**	**0.93**	**0.78**	0.97	0.86	**0.94**	0.83	0.97	0.86
Ratios of RMSFEs when the benchmark model is the AR(p)										
	LINEAR		**BMIDAS**		**EMIDAS**		**PMIDAS**		**UMIDAS**	
	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$
UKCONS	0.96	0.98	0.98	1.00	0.97	**0.97**	0.96	0.97	0.97	**0.97**
UKESI	0.97	0.98	0.95	0.96	0.97	0.98	1.00	1.03	0.97	0.98
UKINDU	0.95	0.96	0.95	1.00	**0.96**	0.99	0.96	**0.97**	**0.96**	0.99
UKSERV	1.06	1.08	1.01**	1.02*	1.04*	1.07	1.03*	1.03*	1.01***	1.01***
UKRETS	0.98	0.98	1.05	1.01	1.02	1.02	1.06	1.03	1.02	1.02
UKBUILD	**0.87**	**0.93**	**0.94**	**0.92**	0.97	1.02	**0.94**	0.98	0.97	1.02

**: p-values of the Diebold-Mariano test*

The out-of-sample estimation results indicate that, like in the ES analysis, not all models are capable to outperform the benchmarks. In particular, the Services and Retail sentiments are not able to beat the benchmarks in almost all kinds of models, while the rest of the sentiment indicators provide, in the majority of the estimations, a ratio lower than one, $r_i < 1$, and thereby seem to be good out-of-sample survey predictors. Surprisingly and unlikely the EU and ES empirical analyses, the CCI does not bring the best out-of-sample predictor among all other survey predictors for all types of models being estimated. This result contradicts the findings of the EU and ES analyses where the CCI was found to be either the best out-of-sample predictor in the MIDAS models or in both the common and mixed frequency models. For the UK analysis, the results however vary. When forecasting one-quarter ahead ($h = 1$), the Building CI brings the best out-of-sample predictor (RMSFE) when the Linear-LS, BMIDAS, and PMIDAS models are estimated, whereas, the Industry CI brings the best out-of-sample predictor when the EMIDAS and UMIDAS models are estimated. Moreover, the MIDAS models seem to provide the highest gains in terms of RMSFE vis-a-vis both benchmarks, $r_i < 1$, as well as the highest gains in terms of RMSFE vis-a-vis the Linear-LS model when the confidence predictor is either the ESI or the Industry CI. On the other hand, when forecasting four-quarters ahead ($h = 4$), the Building CI brings the best out-of-sample predictor (RMSFE) when the Linear-LS and BMIDAS models are estimated, the Industry CI brings the best out-of-sample predictor when the PMIDAS is estimated, and UKCONS brings the best out-of-sample predictor when the EMIDAS and UMIDAS models

are estimated. Moreover, the MIDAS models seem to provide the highest gains in terms of RMSFE vis-a-vis both benchmarks, $r_i < 1$, as well as the highest gains in terms of RMSFE vis-a-vis the Linear-LS model when the confidence predictor is either the ESI or the Consumption CI. Nevertheless note that, the underlying forecasting gains, both for $h = 1$ and $h = 4$, are not statistically significant according to the Diebold-Mariano test.

Finally, when it comes to the one-quarter ahead ($h = 1$) model comparison between the different mixed-frequency aggregation schemes, although it seems that the BMIDAS model with building survey as the predictor beats the other MIDAS aggregation schemes it does not, however, beat the corresponding Linear-LS model. On the other hand, the four-quarters ahead ($h = 4$) model comparison indicates that the BMIDAS model not only outperforms the other MIDAS weighting schemes, but also the common-frequency Linear-LS model. The forecasting gains are, however, not statistically significant. Recall that in the corresponding EU and ES cases, the MIDAS model outperformed both the common-frequency (Linear-LS) and the MIDAS aggregation schemes. Next, in the subsequent subsection, the corresponding UK empirical analysis with financial indicators as predictors is provided.

4.2.3. The role of Financial Indicators (FIs) in the United Kingdom

Similarly with the EU and ES empirical analysis, our second objective is to explore the impact of the Financial Indicators (FI) in describing and anticipating movements in the UK GDP growth through both common and mixed frequency models and once again to compare their performance to the soft UK survey indicators. The related in-sample estimation results of quarterly UK GDP models with financial predictors are reported in Table 13.

Table 13: In-sample estimation results (1995Q1-2019Q4) of the MIDAS regression models when low-frequency variable is quarterly UK GDP and high-frequency predictors are monthly Financial Indicators (FIs) vis-à-vis the corresponding common-frequency Linear-LS models.

	Monthly Frequency of Financial Indicator (FI)							
	BMIDAS				**EMIDAS**			
	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{FI}}$	**BIC**	**LM**	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{FI}}$	**BIC**	**LM**
EASTOXX50	0.479***	0.099***	-0.470	**0.001**	0.480***	0.097**	-0.512	**0.000**
EASTOXX	0.485***	0.099***	-0.482	**0.001**	0.487***	0.095**	-0.524	**0.000**
GEGBY10Y	0.654***	-0.003	-0.421	0.118	**0.662*** **	-0.018	-0.427	0.117
EURIBOR3	0.627***	-0.098***	-0.478	**0.049**	0.633***	-0.101***	-0.527	**0.018**
EURIBOR6	0.653***	-0.101***	-0.480	**0.060**	0.637***	-0.100***	-0.528	**0.024**
EURIBOR12	0.629***	-0.091***	-0.469	0.143	0.647***	-0.098***	-0.527	**0.040**
BRENT	0.660***	-0.058	-0.423	0.256	0.622***	0.035	-0.441	0.533
WTI	**0.671*** **	-0.092	-0.440	0.124	0.640***	0.016	-0.430	0.852
FUTURES	0.664***	-0.088	-0.440	0.127	0.636***	0.017	-0.429	0.889
GOLD	0.625***	-0.096	-0.443	0.169	0.652***	0.016	-0.434	1.000
SILVER	0.642***	-0.084	-0.439	0.134	0.649***	0.007	-0.428	0.993
CORN	0.617***	**-0.121*** **	**-0.523**	**0.087**	0.641***	**-0.142*** **	**-0.547**	0.105
WHEAT	0.666***	-0.102	-0.419	0.285	0.656***	-0.033	-0.461	0.188
	PMIDAS				**UMIDAS**			
	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{FI}}$	**BIC**	**LM**	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{FI}}$	**BIC**	**LM**
EASTOXX50	0.471***	0.101	-0.505	**0.002**	0.626***	0.015	-0.524	1.000
EASTOXX	0.474***	0.100	-0.514	**0.001**	0.614***	0.022	-0.531	0.722

GEGBY10Y	0.654***	-0.003	-0.468	0.118	0.648***	-0.016	-0.505	0.515
EURIBOR3	0.641***	-0.102	-0.525	**0.049**	0.665***	-0.021	-0.535	1.000
EURIBOR6	0.644***	-0.101*	-0.526	**0.062**	0.671***	-0.024	-0.539	1.000
EURIBOR12	0.651***	-0.099*	-0.526	**0.096**	**0.679*** **	**-0.028***	**-0.546**	1.000
BRENT	0.654***	-0.077	-0.453	0.488	0.644***	0.009	-0.520	1.000
WTI	**0.663*** **	-0.102	-0.467	0.274	0.642***	0.014	-0.522	0.580
FUTURES	**0.663*** **	-0.103	-0.467	0.266	0.641***	0.010	-0.520	0.716
GOLD	0.654***	-0.018*	-0.468	0.384	0.652***	0.016	-0.526	1.000
SILVER	0.645***	-0.098	-0.454	0.455	0.649***	0.007	-0.520	0.903
CORN	0.640***	**-0.137**	**-0.546**	0.218	0.644***	0.002	-0.519	1.000
WHEAT	0.656***	-0.033	-0.461	0.342	0.646***	0.001	-0.519	1.000

	Quarterly Frequency of Financial Indicator (FI)		
	LINEAR		
	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{GDP}}$	$\widehat{\boldsymbol{\beta}}_{\boldsymbol{FI}}$	**BIC**
EASTOXX50	0.615***	0.016	-0.525
EASTOXX	0.605***	0.020	-0.529
GEGBY10Y	0.654***	-0.010	-0.501
EURIBOR3	0.695***	-0.030*	-0.547
EURIBOR6	0.701***	-0.034*	-0.554
EURIBOR12	**0.707*** **	**-0.038** **	**-0.564**
BRENT	0.636***	0.009	-0.520
WTI	0.640***	0.005	-0.519
FUTURES	0.640***	0.005	-0.519
GOLD	0.640***	-0.018	-0.530
SILVER	0.649***	-0.006	-0.520
CORN	0.670***	-0.034***	-0.547
WHEAT	0.644***	0.003	-0.519

, **, ***: significance at 10%, 5%, 1% (two-sided p-values)

***LM Test*:= $T(SSR_0^{LS}\text{-}SSR_1^M)/SSR_0^{LS} \xrightarrow{d} \chi^2(r)$**

The following general conclusions can be inferred from Table 13. First, the Euribor interest rate with a maturity of 12 months (EURIBOR12) and the corn oil price (CORN) financial indicators seem to bring the best-fitted models compared to all other financial predictors, depending on the model being estimated. In particular, the EURIBOR12 financial predictor brings the best-fitted model in the case of the common- and mixed-frequency models estimated by LS (Linear-LS and UMIDAS), while the CORN financial predictor brings the best-fitted model in the case of the BMIDAS, EMIDAS, and PMIDAS models. Notably, the fitness of the models does not substantially improve when considering the higher frequency of the soft predictors; it improves slightly (mainly for the UMIDAS models) in the case of the total market Stock Price Index, the Germany government bond yield, the West Texas Intermediate (WTI) oil price, the Crude Oil futures contracts, the prices of the silver precious metals, and the corn prices.

Surprisingly, bias seems to be an important issue in the UK in-sample analysis with financial predictors. Recall that, bias was not found a significant issue in the UK in-sample analysis with survey predictors (as opposed to the EU and ES cases). MIDAS estimations produce statistically significant larger estimated slope coefficients of specific FIs than the corresponding traditional Linear-LS model, revealing the strongest effect of certain FIs on the UK GDP growth, which is omitted when a Linear-LS regression model is estimated instead of the MIDAS model. For instance, the estimated slope coefficient of the total market Stock Price Index (EASTOXX) in the

Linear-LS model is equal to 0.020, whereas, it is much greater when estimated in a MIDAS model; it is appraised to be 0.099, 0.095, and 0.100 when BMIDAS, EMIDAS, and PMIDAS models are estimated, respectively. The bias is strongly supported by the LM statistic. Importantly, there is significant bias in the estimated slope coefficients of the Stock Price Indices and the Euribor interest rates financial predictors when a Linear-LS model is estimated rather than the corresponding BMIDAS, EMIDAS, and PMIDAS models. Note that, likewise in the EU and ES cases, not all Financial Indicators are statistically significant in all kinds of models and the sign of the estimated FI might be either positive or negative, depending on the model being estimated. Next is portrayed the corresponding UK out-of-sample empirical analysis with financial predictors.

4.2.4. Out-of-Sample Forecasting Performance of FIs in the United Kingdom

The corresponding out-of-sample estimation results of quarterly UK GDP models with financial predictors are reported in Table 14, where the ratio of RMSFEs for each Financial Indicator (FI) used in the models is computed once again as follows:

$$r_i = \frac{RMSFE_{predictive\ model,FI_i}}{RMSFE_{benchmark\ model}}$$

where i represents the FI used in the predictive model and i is each individual financial predictor or group-specific combination based on model averaging techniques. In Table 14 the group "Stocks" refers to combinations between the two Stock Price Indices in the case of the Linear-LS and BMIDAS models, and to the total market Stock Price Index in the case of the EMIDAS and UMIDAS models, regardless of the forecasting horizon. In the case of estimating the MIDAS model with polynomial Almon lags (PMIDAS), the subset Euro Stoxx 50 Price Index is preferred when forecasting one-quarter ahead ($h = 1$), while a combination of the two indices is preferred when forecasting four-quarters ahead ($h = 4$). The group "Euribors" refers to combinations between the three interest rates in the case of the Linear-LS, BMIDAS, and PMIDAS models, to the Euribor interest rate with a maturity of 12 months in the case of the EMIDAS models, and to the Euribor interest rate with a maturity of three months in the case of the UMIDAS model when forecasting one-quarter ahead ($h = 1$). On the other hand, forecasting in the long-term shows that a combination of the three euribor interest rates is preferred only for the common-frequency Linear-LS model, while a specific euribor interest rate is chosen depending on the MIDAS model being estimated. Interestingly, like in the EU analysis, the group "Commodities" refers only to individual commodity prices for all kinds of models, as it turns outs that individual forecasts outperform forecasts based on combinations of all commodity predictors. Depending on the model being estimated and to the forecasting horizon (short-term or long-term), a different commodity price brings the best out-of-sample predictor with the lowest ratio of RMSFEs among all commodity predictors. Lastly, recalling our UK one-quarter ahead ($h = 1$) out-of-sample empirical analysis with survey predictors, the group "Sentiments" refers to the Building CI in the case of the Linear-LS, BMIDAS, and PMIDAS models, while it refers to the Industry CI in the case of the EMIDAS and UMIDAS models. On the other hand, the four-quarters ahead ($h = 4$) best out-of-sample predictor is given by the Building CI when the Linear-LS and BMIDAS models are estimated, by the Industry CI when the PMIDAS is estimated, and by the Consumption CI (CCI) when the EMIDAS and UMIDAS models are estimated.

Table 14: Out-of-sample estimation results of the MIDAS regression models when low-frequency variable is quarterly UK GDP and high-frequency predictors are monthly financial and sentiment predictors/combinations vis-à-vis the corresponding common-frequency Linear-LS models.

Ratios of RMSFEs when the benchmark model is the RW										
	LINEAR		**BMIDAS**		**EMIDAS**		**PMIDAS**		**UMIDAS**	
	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$
Stocks	**0.97**	0.83	**0.93**	0.86	0.98	0.91	**0.94**	0.86	**0.96**	**0.82**
Euribors	1.01	0.87	0.98	0.93	0.98	0.85	0.98	0.93	1.00	0.84
Commodities	0.97	**0.81**	0.95	**0.78**	**0.96**	**0.80**	0.98	**0.81**	0.99	0.83
Sentiments	**0.86**	**0.79**	0.93	**0.78**	**0.95**	0.82	**0.94**	0.82	**0.95**	0.82
Ratios of RMSFEs when the benchmark model is the AR(p)										
	LINEAR		**BMIDAS**		**EMIDAS**		**PMIDAS**		**UMIDAS**	
	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$
Stocks	**0.98**	0.99	**0.93**	1.02	0.98	1.08	**0.94**	1.02	**0.97**	**0.97**
Euribors	1.02	1.03	0.98	1.11	0.99	1.01	0.98	1.10	1.00	1.00
Commodities	0.98	**0.96**	0.95	**0.93**	**0.97**	**0.95**	0.98	**0.97**	0.99	0.98
Sentiments	**0.87**	**0.93**	0.94	**0.92**	**0.96**	0.97	**0.94**	0.97	**0.96**	0.97

Forecast Combinations: *Simple mean, Simple median, Least-squares, Mean square error, MSE ranks, smooth AIC weights, and SIC weights.*

Similarly with the EU and ES empirical studies, the out-of-sample estimation results show that almost all models are capable of outperforming the benchmark models; in almost all cases, the forecast combination groups exhibit a ratio lower than one, $r_i < 1$, and are thus considered to be good out-of-sample combined predictors. A few exceptions, however, befall in some estimations. In the case where the benchmark model is the Random Walk (RW) model, the group including combinations of the Euribor interests is an exception when forecasting one-quarter ahead ($h = 1$). Interestingly, when the benchmark model is the Autoregressive (AR(p)) model, the euribor interest rate financial predictors seem to not be good-out-of-sample predictors, especially when forecasting in the long-term ($h = 4$). Note that, the predictive ability of the stock price financial predictors also deteriorates in the long-term. In addition, when it comes to comparing the one-quarter ahead ($h = 1$) predictive ability between the financial groups, it turns out that the "Stocks" financial group brings the best out-of-sample predictor with the lowest RMSFE ratio when both a Linear-LS model and a MIDAS model are estimated, except for the EMIDAS model where the Brent crude oil price brings the best out-of-sample predictor among all other financial predictors. The computed ratios are lower compared to the models with other financial variables/groups as predictors, for both the RW and AR(p) benchmark models. On the other hand, when it comes to comparing the four-quarters ahead ($h = 4$) predictive ability between the financial groups, the "Stocks" financial group brings the best out-of-sample predictor with the lowest RMSFE ratio only when the UMIDAS model is estimated, and the "Commodities" financial group brings the best out-of-sample predictor compared to all other financial group predictors when estimating all other mixed-frequency and the common-frequency model. Hence, it can be palpably affirmed that the Stock Price Indices seem to be strong predictors of economic outlooks for the UK economy regarding the short-term forecasting horizon ($h = 1$), while the Commodity Price Indicators seem to be strong economic outlook predictors for the UK economy concerning the long-term forecasting horizon ($h = 4$).

When emphasizing on evaluating the predictive ability between the common and mixed frequency models, our findings strikingly show that the MIDAS models not only provide the highest gains in terms of RMSFE ratios vis-a-vis the benchmarks but also versus the Linear-LS model, $r_i < 1$, for all financial groups/predictors evaluated (either Stocks, Euribors, or Commodities) and forecasting horizons considered $h = 1$ and $h = 4$). Thereby, the use of financial predictors sturdily supports the mixed-frequency models providing them advantageous forecasting abilities compared to the common-frequency Linear-LS models. Notice that, in the EU and ES short-term and long-term forecasting empirical exercises, the MIDAS models exhibited forecasting gains in comparison to the Linear-LS models only for the two among the three financial groups; Stocks and Euribors, and Euribors and Commodities, respectively. Analytically, the short-term ($h = 1$) forecasting empirical exercise indicated that when the high-frequency financial group predictor is "Stocks", the BMIDAS, PMIDAS, and UMIDAS models provide a lower RMSFE ratio compared to that of the Linear-LS model, when the high-frequency financial group predictor is "Commodities", the BMIDAS and EMIDAS models beat the corresponding Linear-LS model, while when the high-frequency financial group predictor is "Euribors", all MIDAS models outperform the corresponding Linear-LS model. On the other hand, the long-term ($h = 4$) forecasting empirical exercise showed that when the high-frequency financial group predictor is "Stocks", the UMIDAS model provides a lower RMSFE ratio compared to that of the Linear-LS model, when the high-frequency financial group predictor is "Euribors", the EMIDAS and UMIDAS models outperform the corresponding Linear-LS models, and when the high-frequency financial group predictor is "Commodities", the BMIDAS and EMIDAS models beat the corresponding common-frequency models.

Considerably, when it comes to the short-term ($h = 1$) comparison between the best out-of-sample financial predictors and the best out-of-sample confidence predictors, it turns out that all types of models are in favor of the Sentiment predictors, except the BMIDAS model which is in favor of the Financial Stock predictors. That is, the Linear-LS, EMIDAS, PMIDAS, and UMIDAS models provide lower RMSFE ratios when considering the best out-of-sample sentiment predictor vis-à-vis the corresponding common-frequency and mixed-frequency models enhancing the best-out-of-sample financial predictor. Then, when it comes to model comparison between the different MIDAS aggregation schemes, the BMIDAS model with the financial "Stock"-group predictor outperforms all other MIDAS weighting schemes that apparently prefer sentiment predictors. Comparing then the best MIDAS model with the best Linear-LS model – the Linear-LS model with the Building sentiment as a predictor, it turns out that the Linear-LS model beats the BMIDAS model, as well as that the Building sentiment predictor beats the Financial Stock predictors. More precisely, in the case of the RW benchmark model, the ratio of the BMIDAS model is 0.93, while the ratio of the Linear-LS model is 0.86. Similarly, in the case of the AR(p) benchmark model, the ratio of the BMIDAS model is 0.93, while the ratio of the Linear-LS model is 0.87. On the other hand, the long-term ($h = 4$) comparison between the best out-of-sample financial predictors and the best out-of-sample confidence predictors reveals that only the Linear-LS and BMIDAS models are in favor of the Sentiment predictors. In particular, the Linear-LS and BMIDAS models provide lower RMSFE ratios when considering the best out-of-sample sentiment predictor versus the corresponding common- and mixed-frequency models enhancing the best out-of-sample financial predictor. Crucially, comparing the best MIDAS model – the BMIDAS with the Building sentiment predictor and the best Linear-LS model (with the Building sentiment predictor), it turns out that contrary to the short-term comparison, the BMIDAS model, although slightly, beats the Linear-LS model, and that the Building sentiment predictor is preferred as the best four-quarters ahead out-of-sample predictor, irrespective of the frequency enhanced through the models.

In summary, our empirical analysis of forecasting the UK GDP growth using survey and financial predictors reveals the existence of bias of the estimated slope coefficient when a Linear-LS model based on traditional aggregation techniques is estimated rather than a mixed-frequency MIDAS model that considers the time-series behaviour of the data (a finding also of the EU and the ES empirical analyses). Notably, the bias effect is substantially stronger in the case where the soft predictor is a financial predictor. Out-of-sample advantages of the MIDAS models are again at the forefront since MIDAS models are found to exhibit the highest gains in terms of RMSFE vis-a-vis the benchmarks, and thus the highest gains in terms of MSFE vis-a-vis the Linear-LS model when the financial predictors are either Stock prices, Euribor rates, or Commodity prices. However, this does not apply in the case where the predictors are survey confidence indicators. This shows that in the UK case, exploiting the higher frequency of financial data is more important than exploiting the higher frequency of survey data. Recall that, based on our analysis for the EU and ES economies, the CCI is a valuable predictor for their economies and its higher frequency should be exploited. In contrast, the Building sentiment seems to be a more valuable survey predictor for the UK economy compared to both the other sentiments and commonly used financial leading indicators, and employing its higher frequency data does not necessarily improves the forecasts. More precisely, the Linear-LS model outperforms the BMIDAS model in the short-term while slight advantages arise from the higher frequency in the long-term, and importantly, the Building sentiment predictor outperforms the Financial Stock predictors. This is not an outlandish outcome since the construction industry is usually referred to as the “bedrock” of the UK economy representing more than 10% of its total economic outlook, while the preferable low-frequency model for the Building sentiment is related to the slow-moving construction sector.

5. Conclusion

Our study aims to bring to light a shred of new empirical evidence, showing that when the low-frequency process is the GDP growth in the European Union (EU) and the high-frequency soft information is either Survey, Confidence Indicators (CIs) of firms and consumers in the EU, or other Financial Indicators (FIs) commonly used in the literature, estimating a MIDAS model instead of a standard Linear Least Squares (LS) model yields a slope regression estimator with statistically significant higher impact. This reveals, in part, the existence of bias in the estimated slope regression coefficient of the soft predictor in the common frequency model which discards any information about the timing of innovations to the high-frequency soft survey and financial data. The pros of the MIDAS models based on the soft survey and financial data are not only proved in-sample but also out-of-sample; the MIDAS models yield statistically significant and more accurate forecasts of the economic outlook compared to traditional aggregation approaches. Apart from the in-sample and out-of-sample improvements of the mixed-frequency MIDAS models compared to common-frequency Linear-LS models (based on traditional aggregation approaches) which are accomplished through the use of high-frequency ‘soft’ survey and financial data, our analysis discloses through the MIDAS estimations the prominent role of the Consumption Sentiment Indicator as a predictor of the EU economic outlook and other European countries closely related to it, such as Spain, – evidence shown both in-sample and out-of-sample based on bias and efficiency principles. Remarkably, for other economies not closely related to the EU, such as the United Kingdom, the Building Sentiment Indicator seems to have a primary role for the UK economy and it is mainly exploited through common-frequency estimations. Lastly, although the Stock Price Indices seem to have a strong leading ability compared to other financial predictors – evidence found for all three investigated economies (EU, ES, and UK), the sentiment predictors seem to outperform the financial ones.

References

Andreou, E., E. Ghysels, and A. Kourtellos. 2010. “Regression models with mixed sampling frequencies.” *Journal of Econometrics* 158: 246–261.

Andreou, E., E. Ghysels, and A. Kourtellos. 2013. “Should Macroeconomic Forecasters Use Daily Financial Data and How?” *Journal of Business & Economic Statistics* 31: 240–251.

Andreou, E. 2016. “On the use of high frequency measures of volatility in MIDAS regressions.” *Journal of Econometrics* 193: 367–389.

Angelini, E., G. Camba-Mendez, D. Giannone, L. Reichlin, and G. Rünstler. 2011. “Short-term forecasts of euro area GDP growth.” *The Econometrics Journal* 14: C25–C44.

Armesto, M. T., K. M. Engemann, and M. T. Owyang. 2010. “Forecasting With Mixed Frequencies.” *Federal Reserve Bank of St. Louis Review* 92: 521–536.

Aruoba, S. B., F. X. Diebold, and C. Scotti. 2009. “Real-Time Measurement of Business Conditions.” *Journal of Business & Economic Statistics* 27: 417–427.

Bánbura, M. and G. Rünstler. 2011. “A look into the factor model black box: Publication lags and the role of hard and soft data in forecasting GDP.” *International Journal of Forecasting* 27: 333–346.

Barsky, R. B., and E. R. Sims. 2012. “Information, Animal Spirits, and the Meaning of Innovations in Consumer Confidence.” *American Economic Review* 102: 1343–1377.

Barsoum, F., and S. Stankiewicz. 2015. “Forecasting GDP growth using mixed-frequency models with switching regimes.” *International Journal of Forecasting* 31: 33–50.

Batchelor, R., and P. Dua. 1998. “Improving macro-economic forecasts. The role of consumer confidence.” International Journal of Forecasting 14: 71–81.

Brewer, K. R. W. 1973. “Some consequences of temporal aggregation and systematic sampling for ARMA and ARMAX models.” *Journal of Econometrics* 1: 133–154.

Camacho, M., and G. Perez-Quiros. 2010. “Introducing the EURO-STING: Short Term Indicator of Euro Area Growth.” *Journal of Applied Econometrics* 25: 663–694.

Christiansen, C., J. N. Eriksen, and S. V. Møller. 2014. “Forecasting US recessions: The role of sentiment.” *Journal of Banking & Finance* 49: 459–468.

Clavería, G. Ó. 2021. “Forecasting with business and consumer survey data.” *Journal of Forecasting* 3: 113–134.

Clements, M. P., and A. B. Galvão. 2008. “Macroeconomic Forecasting With Mixed Frequency Data: Forecasting Output Growth in the United States.” *Journal of Business and Economic Statistics* 26: 546–554.

Clements, M. P., and A. B. Galvão. 2009. “Forecasting US output growth using Leading Indicators: An appraisal using MIDAS models.” *Journal of applied econometrics* 24: 1187–1206.

Conrad, C., and M. Schienle. 2020. “Testing for an Omitted Multiplicative Long-Term Component in GARCH Models.” *Journal of Business & Economic Statistics* 38: 229–242.

Conrad, C., and O. Kleen. 2020. “Two are better than one: Volatility forecasting using multiplicative component GARCH-MIDAS models.” *Journal of Applied Econometrics* 35: 19–45.

De Bondt, G. J., and E. Hahn. 2014. “Introducing the Euro Area-wide Leading Indicator (ALI): Real-Time Signals of Turning Points in the Growth Cycle from 2007 to 2011.” *Journal of Forecasting* 33: 47–68.

Dees, S., and P. S. Brinca. 2013. “Consumer confidence as a predictor of consumption spending: Evidence for the United States and the Euro area.” *International Economics* 134: 1–14.

Diebold, F. X., and R. S. Mariano. 2002. “Comparing Predictive Accuracy.” Journal of Business & Economic Statistics 20: 134–144.

Eggers, A. C., M. Ellison, and S. S. Lee. 2021. “The economic impact of recession announcements.” *Journal of Monetary Economics* 120: 40–52.

Engle, R. F., and T.-C. Liu. 1972. “Effects of Aggregation Over Time on Dynamic Characteristics of An Econometric Model.” In: *Hickman, B., Hickman, Bert G. (Eds.), Econometric Models of Cyclical Behavior*. *NBER*, pp. 673–738.

Ferrara, L., and C. Marsilli. 2013. “Financial variables as leading indicators of GDP growth: Evidence from a MIDAS approach during the Great Recession.” *Applied Economics Letters* 20: 233–237.

Foroni, C., M. Marcellino, and C. Schumacher. 2015. “Unrestricted mixed data sampling (MIDAS): MIDAS regressions with unrestricted lag polynomials.” *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 178: 57–82.

Geweke, J. 1978. “Temporal aggregation in the multiple regression model.” *Econometrica* 46: 643–661.

Ghysels, E., and H. Qian. 2019. “Estimating MIDAS regressions via OLS with polynomial parameter profiling.” *Econometrics and Statistics* 9: 1–16.

Ghysels, E. and J. H. Wright. 2009. “Forecasting Professional Forecasters.” *Journal of Business & Economic Statistics* 27: 504–516.

Ghysels, E., and M. Marcellino. 2018. “Applied economic forecasting using time series methods.” New York, NY: Oxford University Press.

Ghysels, E., and R. Valkanov. 2012. “Forecasting Volatility With MIDAS.” In Handbook of Volatility Models and Their Applications, eds. L. Bauwens, C. Hafner, and S. Laurent, Hoboken, NJ: Wiley, pp. 383–401.

Ghysels, E., A. Sinko, and R. Valkanov. 2007. “MIDAS Regressions: Further Results and New Directions.” *Econometric Reviews* 26: 53-90.

Ghysels, E., P. Santa-Clara, and R. Valkanov. 2004. “The MIDAS touch: Mixed Data Sampling Regressions.” Discussion paper, University of North Carolina and UCLA.

Ghysels, E., P. Santa-Clara, and R. Valkanov. 2006. “Predicting volatility: getting the most out of return data sampled at different frequencies.” *Journal of Econometrics* 131: 59–95.

Girardi, A., C. Gayer, and A. Reuter. 2015. “The Role of Survey Data in Nowcasting Euro Area GDP Growth.” *Journal of Forecasting* 35: 400–418.

Hsiao, C. 1979. “Linear regression using both temporally aggregated and temporally disaggregated data.” *Journal of Econometrics* 10: 243–252.

Jongrim, H., and S. Inhwan. November 2021. “Global Confidence, Uncertainty, and Business Cycles.” Available at SSRN: https://ssrn.com/abstract=3748156 or http://dx.doi.org/10.2139/ssrn.3748156.

Kuzin, V., M. Marcellino, and C. Schumacher. 2011. “MIDAS vs. mixed-frequency VAR: Nowcasting GDP in the euro area.” *International Journal of Forecasting* 27: 529–542.

Lewis, D., K. Mertens, J. H. Stock, and M. Trivedi. 2022. “Measuring real activity using a weekly economic index.” *Journal of Applied Econometrics* 37: 667–687.

Lundbergh, S. and T. Teräsvirta. 2002. “Evaluating GARCH models.” *Journal of Econometrics* 110: 417–435.

Matsusaka, J. G. and A. M. Sbordone. 1995. “Consumer Confidence and Economic Fluctuations.” *Economic Enquiry* 33: 296–318.

Monteforte, L., and G. Moretti. 2013. “Real Time Forecasts of Inflation: The Role of Financial Variables.” *Journal of Forecasting* 32: 51–61.

Schwarz, G. 1978. “Estimating the dimension of a model.” *The Annals of Statistics* 6: 461–464.

Tkacova, A., B. Gavurova, and M. Behun. 2017. “The Composite Leading Indicator for German Business Cycle.” *Journal of Competitiveness* 9: 114–133.

Appendix

Table 1: Variable Description (acronyms, definition, source, frequency, transformations) over the sample period 1995Q1-2019Q4.

Acronym	Definition & Data Source	Frequency & Transformation
EUGDP	GDP growth in the EU (Eurostat)	Quarterly growth rate
ESGDP	GDP growth in the ES (Eurostat)	
UKGDP	GDP growth in the UK (Office for National Statistics)	
Confidence Indicators (European Commission)		
ESI	Economic Sentiment Indicator in the EU, ES, and UK	Monthly and Quarterly Δ
INDU	Industry Confidence Indicator in the EU, ES, and UK	
INDU_q2	Assessment of order-book levels in the EU	
INDU_q4	Assessment of stocks of finished products in the EU	
INDU_q5	Production expectations for the months ahead in the EU	
SERV	Services Confidence Indicator in the EU, ES, and UK	
SERV_q1	Business situation development over the past 3 months in the EU	
SERV_q2	Evolution of the demand over the past 3 months in the EU	
SERV_q3	Expectation of the demand over the next 3 months in the EU	
CONS	Consumption Confidence Indicator in the EU, ES, and UK	
CONS_q1	Financial situation over last 12 months in the EU	
CONS_q2	Financial situation over next 12 months in the EU	
CONS_q4	General economic situation over next 12 months in the EU	
CONS_q9	Major purchases over next 12 months in the EU	
RETS	Retail Confidence Indicator in the EU, ES, and UK	
RETS_q1	Business activity (sales) development over the past 3 months in the EU	
RETS_q2	Volume of stock currently hold in the EU	
RETS_q4	Business activity expectations over the next 3 months in the EU	
BUILD	Construction Confidence Indicator in the EU, ES, and UK	
BUILD_q3	Evolution of your current overall order books in the EU	
BUILD_q4	Employment expectations over the next 3 months in the EU	
Financial Indicators		
EASTOXX50	Euro area (changing composition) Dow Jones Euro Stoxx 50 Price Index (ECB)	Monthly and Quarterly log-return
EASTOXX	Euro area (changing composition) Dow Jones Euro Stoxx Price Index (ECB)	
GEGBY10Y	Germany 10-year Government Benchmark Bond Yield (DataStream)	Monthly and Quarterly Δ
EURIBOR3	Euro area (changing composition) Euribor 3-month (ECB)	
EURIBOR6	Euro area (changing composition) Euribor 6-month (ECB)	
EURIBOR12	Euro area (changing composition) Euribor 1-year (ECB)	
BRENT	Brent Crude Oil (€)-Commodity Prices (Global Financial Data (GFD))	Monthly and Quarterly log-return
WTI	West Texas Intermediate Oil Price (€/Barrel)-Commodity Prices (GFD)	
FUTURES	Crude Oil Futures (€)-Futures Contracts (GFD)	
GOLD	Gold Bullion Price-New York (€/Ounce)-Commodity Price (GFD)	
SILVER	Silver Cash Price (€/Ounce)-Commodity Prices (GFD)	
CORN	Corn Oil Price, Wet Mill, Chicago (Cents/Pound) (€)-Commodity Prices (GFD)	
WHEAT	Wheat #2 Cash Price (€/Bushel)-Commodity Prices (GFD)	

Table 2a: Correlation Matrix between the EU GDP growth and the independent variables (1995Q1-2019Q4)

Independent variables are given by either Sentiment Indicators in the EU or Financial Indicators

	EUGDP	EUESI	EUINDU	EUSERV	EUCONS	EURETS	EUBUILD
EUGDP	1.000	0.559	0.605	0.462	0.312	0.378	0.618
EUESI	0.559	1.000	0.942	0.899	0.716	0.672	0.664
EUINDU	0.605	0.942	1.000	0.763	0.551	0.570	0.639
EUSERV	0.462	0.899	0.763	1.000	0.600	0.621	0.615
EUCONS	0.312	0.716	0.551	0.600	1.000	0.559	0.450
EURETS	0.378	0.672	0.570	0.621	0.559	1.000	0.326
EUBUILD	**0.618**	0.664	0.639	0.615	0.450	0.326	1.000

	EUGDP	EASTOXX50	EASTOXX	GEGBY10Y	EURIBOR3	EURIBOR6	EURIBOR12	BRENT	WTI	FUTURES	GOLD	SILVER	CORN	WHEAT
EUGDP	1.000	0.417	0.426	0.288	0.652	0.651	0.624	0.266	0.262	0.270	-0.110	0.158	0.226	0.148
EASTOXX50	0.417	1.000	0.991	0.299	0.142	0.181	0.234	0.348	0.353	0.354	-0.006	0.260	0.133	0.029
EASTOXX	0.426	0.991	1.000	0.315	0.153	0.195	0.253	0.364	0.366	0.366	0.005	0.284	0.159	0.019
GEGBY10Y	0.288	0.299	0.315	1.000	0.322	0.412	0.507	0.388	0.371	0.376	-0.246	-0.013	0.137	0.002
EURIBOR3	**0.652**	0.142	0.153	0.322	1.000	0.982	0.933	0.189	0.205	0.213	-0.119	-0.051	0.094	0.056
EURIBOR6	0.651	0.181	0.195	0.412	0.982	1.000	0.979	0.234	0.249	0.257	-0.123	-0.040	0.090	0.046
EURIBOR12	0.624	0.234	0.253	0.507	0.933	0.979	1.000	0.279	0.287	0.294	-0.086	-0.010	0.087	0.014
BRENT	0.266	0.348	0.364	0.388	0.189	0.234	0.279	1.000	0.959	0.955	0.124	0.322	0.237	0.043
WTI	0.262	0.353	0.366	0.371	0.205	0.249	0.287	0.959	1.000	0.999	0.076	0.240	0.200	0.013
FUTURES	0.270	0.354	0.366	0.376	0.213	0.257	0.294	0.955	0.999	1.000	0.068	0.230	0.195	0.014
GOLD	-0.110	-0.006	0.005	-0.246	-0.119	-0.123	-0.086	0.124	0.076	0.068	1.000	0.669	0.082	0.199
SILVER	0.158	0.260	0.284	-0.013	-0.051	-0.040	-0.010	0.322	0.240	0.230	0.669	1.000	0.240	0.214
CORN	0.226	0.133	0.159	0.137	0.094	0.090	0.087	0.237	0.200	0.195	0.082	0.240	1.000	0.259
WHEAT	0.148	0.029	0.019	0.002	0.056	0.046	0.014	0.043	0.013	0.014	0.199	0.214	0.259	1.000

Table 2b: Correlation Matrix between the ES GDP growth and the independent variables (1995Q1-2019Q4)

Independent variables are given by either Sentiment Indicators in the ES or Financial Indicators

	ESGDP	ESESI	ESINDU	ESSERV	ESCONS	ESRETS	ESBUILD
ESGDP	1.000	0.213	0.274	0.118	0.147	-0.088	0.158
ESESI	0.213	1.000	0.863	0.687	0.669	0.490	0.301
ESINDU	**0.274**	0.863	1.000	0.348	0.400	0.210	0.217
ESSERV	0.118	0.687	0.348	1.000	0.530	0.563	0.111
ESCONS	0.147	0.669	0.400	0.530	1.000	0.507	0.222
ESRETS	-0.088	0.490	0.210	0.563	0.507	1.000	0.136
ESBUILD	0.158	0.301	0.217	0.111	0.222	0.136	1.000

	ESGDP	EASTOXX50	EASTOXX	GEGBY10Y	EURIBOR3	EURIBOR6	EURIBOR12	BRENT	WTI	FUTURES	GOLD	SILVER	CORN	WHEAT
ESGDP	1.000	0.344	0.346	0.245	0.477	0.487	0.474	0.167	0.190	0.196	-0.153	0.022	0.194	0.009
EASTOXX50	0.344	1.000	0.991	0.299	0.142	0.181	0.234	0.348	0.353	0.354	-0.006	0.260	0.133	0.029
EASTOXX	0.346	0.991	1.000	0.315	0.153	0.195	0.253	0.364	0.366	0.366	0.005	0.284	0.159	0.019
GEGBY10Y	0.245	0.299	0.315	1.000	0.322	0.412	0.507	0.388	0.371	0.376	-0.246	-0.013	0.137	0.002
EURIBOR3	0.477	0.142	0.153	0.322	1.000	0.982	0.933	0.189	0.205	0.213	-0.119	-0.051	0.094	0.056
EURIBOR6	**0.487**	0.181	0.195	0.412	0.982	1.000	0.979	0.234	0.249	0.257	-0.123	-0.040	0.090	0.046
EURIBOR12	0.474	0.234	0.253	0.507	0.933	0.979	1.000	0.279	0.287	0.294	-0.086	-0.010	0.087	0.014
BRENT	0.167	0.348	0.364	0.388	0.189	0.234	0.279	1.000	0.959	0.955	0.124	0.322	0.237	0.043
WTI	0.190	0.353	0.366	0.371	0.205	0.249	0.287	0.959	1.000	0.999	0.076	0.240	0.200	0.013
FUTURES	0.196	0.354	0.366	0.376	0.213	0.257	0.294	0.955	0.999	1.000	0.068	0.230	0.195	0.014
GOLD	-0.153	-0.006	0.005	-0.246	-0.119	-0.123	-0.086	0.124	0.076	0.068	1.000	0.669	0.082	0.199
SILVER	0.022	0.260	0.284	-0.013	-0.051	-0.040	-0.010	0.322	0.240	0.230	0.669	1.000	0.240	0.214
CORN	0.194	0.133	0.159	0.137	0.094	0.090	0.087	0.237	0.200	0.195	0.082	0.240	1.000	0.259
WHEAT	0.009	0.029	0.019	0.002	0.056	0.046	0.014	0.043	0.013	0.014	0.199	0.214	0.259	1.000

Table 2c: Correlation Matrix between the UK GDP growth and the independent variables (1995Q1-2019Q4)

Independent variables are given by either Sentiment Indicators in the UK or Financial Indicators

	UKGDP	UKESI	UKINDU	UKSERV	UKCONS	UKRETS	UKBUILD
UKGDP	1.000	0.403	0.365	0.260	0.202	0.151	0.453
UKESI	0.403	1.000	0.879	0.787	0.605	0.620	0.524
UKINDU	0.365	0.879	1.000	0.508	0.361	0.451	0.458
UKSERV	0.260	0.787	0.508	1.000	0.405	0.468	0.299
UKCONS	0.202	0.605	0.361	0.405	1.000	0.535	0.425
UKRETS	0.151	0.620	0.451	0.468	0.535	1.000	0.303
UKBUILD	**0.453**	0.524	0.458	0.299	0.425	0.303	1.000

	UKGDP	EASTOXX50	EASTOXX	GEGBY10Y	EURIBOR3	EURIBOR6	EURIBOR12	BRENT	WTI	FUTURES	GOLD	SILVER	CORN	WHEAT
UKGDP	1.000	0.427	0.446	0.159	0.353	0.353	0.346	0.295	0.296	0.297	-0.071	0.116	0.339	0.129
EASTOXX50	0.427	1.000	0.991	0.299	0.142	0.181	0.234	0.348	0.353	0.354	-0.006	0.260	0.133	0.029
EASTOXX	**0.446**	0.991	1.000	0.315	0.153	0.195	0.253	0.364	0.366	0.366	0.005	0.284	0.159	0.019
GEGBY10Y	0.159	0.299	0.315	1.000	0.322	0.412	0.507	0.388	0.371	0.376	-0.246	-0.013	0.137	0.002
EURIBOR3	0.353	0.142	0.153	0.322	1.000	0.982	0.933	0.189	0.205	0.213	-0.119	-0.051	0.094	0.056
EURIBOR6	0.353	0.181	0.195	0.412	0.982	1.000	0.979	0.234	0.249	0.257	-0.123	-0.040	0.090	0.046
EURIBOR12	0.346	0.234	0.253	0.507	0.933	0.979	1.000	0.279	0.287	0.294	-0.086	-0.010	0.087	0.014
BRENT	0.295	0.348	0.364	0.388	0.189	0.234	0.279	1.000	0.959	0.955	0.124	0.322	0.237	0.043
WTI	0.296	0.353	0.366	0.371	0.205	0.249	0.287	0.959	1.000	0.999	0.076	0.240	0.200	0.013
FUTURES	0.297	0.354	0.366	0.376	0.213	0.257	0.294	0.955	0.999	1.000	0.068	0.230	0.195	0.014
GOLD	-0.071	-0.006	0.005	-0.246	-0.119	-0.123	-0.086	0.124	0.076	0.068	1.000	0.669	0.082	0.199
SILVER	0.116	0.260	0.284	-0.013	-0.051	-0.040	-0.010	0.322	0.240	0.230	0.669	1.000	0.240	0.214
CORN	0.339	0.133	0.159	0.137	0.094	0.090	0.087	0.237	0.200	0.195	0.082	0.240	1.000	0.259
WHEAT	0.129	0.029	0.019	0.002	0.056	0.046	0.014	0.043	0.013	0.014	0.199	0.214	0.259	1.000

Table 3a: Descriptive statistics of EU Confidence Indicators.

	EUESI	EUINDU	EUSERV	EUCONS	EURETS	EUBUILD
Mean	-0.009	-0.007	0.000	-0.004	0.006	-0.011
Median	0.110	0.057	0.032	0.078	0.050	0.063
Maximum	4.399	4.381	3.606	3.676	4.135	3.081
Minimum	-12.758	-11.155	-10.806	-10.191	-7.681	-6.011
Std. Dev.	1.100	1.102	1.000	1.055	1.030	0.786
Skewness	-4.770	-3.303	-3.892	-2.807	-1.255	-1.257
Kurtosis	59.765	36.287	45.881	30.485	14.224	13.645
Jarque-Bera	43900.65	15259.28	25166.45	10426.54	1752.69	1585.17
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Sum	-2.905	-2.142	0.000	-1.385	1.843	-3.579
Sum Sq. Dev.	383.331	385.001	317.000	352.637	336.374	195.680
Observations	318	318	318	318	318	318

Table 3b: Descriptive statistics of EU Industry Confidence Indicators.

	EUINDU	EUINDU_q2	EUINDU_q4	EUINDU_q5
Mean	0.000	0.000	0.000	0.000
Median	0.031	0.017	0.033	0.022
Maximum	4.381	4.073	3.579	7.715
Minimum	-11.155	-8.211	-3.158	-11.638
Std. Dev.	1.000	1.000	1.000	1.000
Skewness	-3.195	-1.422	-0.022	-2.244
Kurtosis	38.791	14.195	3.540	54.765
Jarque-Bera	24289.02	2451.51	5.40	49608.85
Probability	0.000	0.000	0.067	0.000
Sum	0.000	0.000	0.000	0.000
Sum Sq. Dev.	440.000	440.000	440.000	440.000
Observations	441	441	441	441

Table 3c: Descriptive statistics of EU Services Confidence Indicators.

	EUSERV	EUSERV_q1	EUSERV_q2	EUSERV_q3
Mean	0.000	0.000	0.000	0.000
Median	0.032	0.049	0.000	0.008
Maximum	3.606	3.832	3.827	5.683
Minimum	-10.806	-8.487	-8.374	-9.619
Std. Dev.	1.000	1.000	1.000	1.000
Skewness	-3.892	-1.901	-1.616	-2.088
Kurtosis	45.881	20.813	20.086	36.292
Jarque-Bera	25166.45	4395.70	4006.62	14916.83
Probability	0.000	0.000	0.000	0.000
Sum	0.000	0.000	0.000	0.000
Sum Sq. Dev.	317.000	317.000	317.000	317.000
Observations	318	318	318	318

Table 3d: Descriptive statistics of EU Consumption Confidence Indicators.

	EUCONS	EUCONS_q1	EUCONS_q2	EUCONS_q4	EUCONS_q9
Mean	0.000	0.000	0.000	0.000	0.000
Median	0.078	0.115	0.091	-0.007	-0.008
Maximum	3.676	4.388	3.796	4.140	2.671
Minimum	-10.191	-4.676	-12.097	-8.821	-7.325
Std. Dev.	1.000	1.000	1.000	1.000	1.000
Skewness	-2.508	-0.504	-3.914	-1.606	-0.734
Kurtosis	28.187	5.119	51.224	19.251	8.874
Jarque-Bera	12119.26	101.19	43858.37	5042.14	673.61
Probability	0.000	0.000	0.000	0.000	0.000
Sum	0.000	0.000	0.000	0.000	0.000
Sum Sq. Dev.	440.000	440.000	440.000	440.000	440.000
Observations	441	441	441	441	441

Table 3e: Descriptive statistics of EU Retail Confidence Indicators.

	EURETS	EURETS_q1	EURETS_q2	EURETS_q4
Mean	0.000	0.000	0.000	0.000
Median	0.033	-0.022	-0.018	0.013
Maximum	4.135	3.534	4.072	4.935
Minimum	-7.681	-5.257	-3.459	-7.959
Std. Dev.	1.000	1.000	1.000	1.000
Skewness	-1.022	-0.435	0.295	-0.805
Kurtosis	12.320	6.475	5.118	14.904
Jarque-Bera	1638.70	230.96	87.00	2597.29
Probability	0.000	0.000	0.000	0.000
Sum	0.000	0.000	0.000	0.000
Sum Sq. Dev.	431.000	431.000	431.000	431.000
Observations	432	432	432	432

Table 3f: Descriptive statistics of EU Building Confidence Indicators.

	EUBUILD	EUBUILD_q3	EUBUILD_q4
Mean	0.000	0.000	0.000
Median	0.063	0.048	0.026
Maximum	3.081	3.120	3.091
Minimum	-6.011	-3.551	-6.308
Std. Dev.	1.000	1.000	1.000
Skewness	-0.827	-0.365	-0.526
Kurtosis	7.382	4.885	7.304
Jarque-Bera	403.16	75.08	360.70
Probability	0.000	0.000	0.000
Sum	0.000	0.000	0.000
Sum Sq. Dev.	440.000	440.000	440.000
Observations	441	441	441

Table 4: Descriptive statistics of ES Confidence Indicators.

	ESESI	ESINDU	ESSERV	ESCONS	ESRETS	ESBUILD
Mean	0.004	0.009	0.000	0.004	0.013	0.004
Median	0.050	0.008	0.016	0.000	0.007	-0.053
Maximum	3.548	3.694	3.573	3.206	4.034	3.975
Minimum	-9.779	-8.369	-7.729	-7.236	-8.235	-2.739
Std. Dev.	0.999	1.018	1.000	0.980	0.974	0.986
Skewness	-2.864	-1.627	-1.292	-1.248	-1.762	0.444
Kurtosis	33.005	17.498	14.615	12.573	20.135	4.305
Jarque-Bera	11663.56	2759.99	1769.75	1223.35	3825.36	31.14
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Sum	1.288	2.608	0.000	1.335	3.791	1.342
Sum Sq. Dev.	298.171	310.033	299.000	287.016	283.430	290.508
Observations	300	300	300	300	300	300

Table 5: Descriptive statistics of UK Confidence Indicators.

	UKESI	UKINDU	UKSERV	UKCONS	UKRETS	UKBUILD
Mean	-0.010	-0.005	0.007	-0.006	-0.007	-0.005
Median	0.045	-0.037	0.020	-0.035	-0.016	-0.004
Maximum	2.875	2.819	2.427	3.010	3.014	3.611
Minimum	-2.485	-2.804	-2.942	-3.323	-4.041	-3.432
Std. Dev.	0.877	0.983	0.915	0.865	1.116	1.023
Skewness	0.104	0.056	-0.165	0.157	-0.101	0.114
Kurtosis	3.309	2.853	3.258	4.454	3.099	4.585
Jarque-Bera	1.58	0.39	1.99	25.17	0.57	29.17
Probability	0.454	0.825	0.369	0.000	0.751	0.000
Sum	-2.850	-1.371	1.968	-1.587	-1.933	-1.340
Sum Sq. Dev.	209.105	262.995	227.603	203.466	339.061	284.561
Observations	273	273	273	273	273	273

Table 6: Descriptive statistics of Financial Indicators.

	EASTOXX50	EASTOXX	GEGBY10Y	EURIBOR3	EURIBOR6	EURIBOR12
Mean	0.001	0.009	0.000	0.000	-0.013	-0.030
Median	0.125	0.135	-0.037	0.141	0.113	0.073
Maximum	2.417	2.556	3.272	6.216	5.204	3.202
Minimum	-5.975	-6.047	-2.931	-5.656	-5.832	-5.741
Std. Dev.	1.007	1.015	1.000	1.001	0.995	0.981
Skewness	-1.231	-1.392	0.241	-0.930	-1.500	-1.602
Kurtosis	7.652	8.359	3.202	16.258	14.260	11.306
Jarque-Bera	370.525	487.832	3.660	2,397.163	1,816.288	1,060.044
Probability	0.000	0.000	0.160	0.000	0.000	0.000
Sum	0.178	3.031	0.000	-0.104	-4.142	-9.684
Sum Sq. Dev.	324.752	329.899	320.000	320.937	316.598	308.052
Observations	321	321	321	321	321	321

	BRENT	WTI	FUTURES	GOLD	SILVER	CORN	WHEAT
Mean	0.028	0.030	0.030	0.045	0.042	0.030	0.022
Median	0.064	0.142	0.138	-0.011	-0.029	0.071	0.040
Maximum	4.776	5.418	5.562	3.298	3.004	2.834	3.103
Minimum	-9.317	-7.081	-7.107	-2.474	-2.887	-3.502	-4.183
Std. Dev.	1.012	0.983	0.974	0.951	0.966	0.941	1.054
Skewness	-2.158	-0.913	-0.815	0.472	0.131	-0.193	-0.269
Kurtosis	26.305	13.858	14.317	3.821	3.267	4.531	4.250
Jarque-Bera	7,513.041	1,621.277	1,748.618	20.942	1.869	33.320	24.771
Probability	0.000	0.000	0.000	0.000	0.393	0.000	0.000
Sum	9.011	9.604	9.636	14.428	13.416	9.761	6.978
Sum Sq. Dev.	327.763	308.910	303.294	289.312	298.879	283.628	355.547
Observations	321	321	321	321	321	321	321