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Forecasting Private Consumption by Consumer Surveys

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ABSTRACT
Survey-based indicators are widely seen as leading indicators for economic activity. As such, consumer confidence might be informative for the future path of private consumption. Although the indicators receive high attention in the media, their forecasting power often appears to be very limited. This paper takes a fresh look at the data that serve as a basis for the consumer confidence indicator (CCI) reported by the EU Commission for the euro area. Different pooling methods are applied to exploit the survey information. Forecasts are based on mixed data sampling (MIDAS) and bridge equations. While the CCI does not outperform the autoregressive benchmark, the new indicators are able to raise forecasting performance. The best performing indicator should be built upon pre-selection methods. Data-driven aggregation methods should be preferred to determine the weights of the individual ingredients. Copyright © 2011 John Wiley & Sons, Ltd.

KEY WORDS consumer confidence; consumption; nowcasting; mixed-frequency data

INTRODUCTION

Survey-based confidence indicators are often seen as leading signals for real economic activity. The attention these indicators receive in the media refers to the potential information they provide regarding current and future economic developments. As such, the consumer confidence indicator (CCI) reported by the European Commission for the euro area and individual countries is widely used by economic agents to assess the future path of private consumption (Dominitz and Manski, 2004). Significant changes in the CCI can provide valuable information for businesses regarding to what extent households are willing to make new purchases.

Despite the great attention the CCI receives when it is published, there is no consensus with regard to the actual contribution of the CCI to predict private consumption. Carroll *et al.* (1994) and Bram and Ludvigson (1998) have provided evidence that lagged values of the CCI can improve short-term forecasts for consumption in the USA to some extent, while Acemoglu and Scott (1994) and Easaw *et al.* (2005) have reported similar results for the UK. Ludvigson (2004) has argued that much of the survey information is already included in fundamental economic and financial indicators, such as labour income, real share prices and short-term interest rates. Likewise, Croushore (2005) has demonstrated that the levels of sentiment indicators are not able to supply any additional information to the nowcast of US consumption. The CCI may have only incremental power in conditional regression models. According to Nahuis and Jansen (2004), forecasting performance can be improved in some cases, if the CCI is combined with measures of retailer confidence. Hence, not only the perceptions of buyers should be taken into account but also the perceptions of the sellers of consumer goods.

Although the predictive ability of consumer confidence appears to be very limited, the CCI is available on a timely basis and can therefore provide a preliminary estimate of year-on-year consumption growth in the current period. Moreover, the information embedded in the consumer survey may be exploited in different ways. In fact, a modest forecasting performance might reflect inappropriate pooling techniques. The CCI is obtained as a composite index of the responses of households to different questions. According to Jonsson and Lindén (2009), a micro indicator based on questions related to the individual household situation might be able to outperform the CCI. Households seem to have better knowledge of their own economic situation compared to the general economic situation.

This paper takes a similar route. It derives a composite indicator for the euro area, where alternative pooling methods are applied to the consumer survey data. Given that the information is available at a monthly frequency, whereas private consumption is published quarterly, different strategies can be used to link them. A popular method is to use the so-called bridge equations by aggregating the survey data to the quarterly frequency. Alternatively, information can be used as soon as it is available by employing mixed-data sampling (MIDAS) equations. In that case, monthly data are used directly to predict current-quarter consumption growth.

The information is extracted in the best possible way to render the optimal indicator in terms of its forecasting performance. Weighting schemes vary from simple averages of the forecasts implied by the individual questions of the consumer survey, through principal components, to weights based on past correlations or forecast accuracy. Furthermore, pre-selection methods are applied.

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The CCI does not outperform the autoregressive benchmark in many cases. However, carefully constructed indicators are able to increase forecasting performance and the gains are often significant. Hence, composite indicators based on data-driven weighting methods turn out to be useful to predict consumption growth. This result does not mean that accurate forecasts for private consumption can be derived from the survey information alone. It only implies that the CCI of the European Commission can be improved, if the survey data are exploited properly. To achieve this result, the composite indicator should be built on pre-selection methods, while data-driven aggregation methods should be applied to determine the weights of individual ingredients.

The rest of the paper is organized as follows. The next section reviews the arguments on why an impact of consumer confidence on private consumption should be expected. The approach to measure consumer confidence in the euro area is discussed in the third section. The fourth section presents the econometric methodology and the fifth section reports the empirical results. The sixth section concludes. The questionnaire for the consumer survey is included as an Appendix.

CONSUMER CONFIDENCE AND PRIVATE CONSUMPTION

The role of consumer confidence in explaining the development of private consumption is not obvious. A long-run impact can be ruled out in advance, as households cannot be excessively confident forever. Therefore, any impact is restricted to the short run, implying that consumer confidence behaves like a stationary variable. But even an influence in the short run can be doubted. According to the life cycle permanent income hypothesis, private consumption depends on permanent rather than on current income. If agents form their expectations in a rational way, changes in consumption cannot be anticipated, since they are purely random (Hall, 1978). Thus, confidence does not play any role in forecasting consumption.

Nonetheless, previous research has pointed out to substantial deviations from the permanent income hypothesis; see the seminal contributions of Flavin (1991), Campbell and Mankiw (1991), and Deaton (1992). In the presence of liquidity constraints, confidence may increase in advance of consumption owing to the delay in obtaining credit for consumption spending to take place. As consumer confidence focuses on the willingness to pay, it can provide some information not embedded in other variables. Due to the liberalization of financial markets, however, liquidity constraints have become less binding, leading to a decline in the impact of consumer confidence on consumption (see Al Eyd *et al.*, 2009).

Eppright *et al.* (1998) discussed psychological arguments why consumer confidence can affect consumption behavior. Sentiment might explain changes in consumption in periods of uncertainty and extraordinary events. The CCI can reflect the expected impact of shocks, when no sufficient information is available from the past. Negative shocks can worsen confidence due to self-fulfilling prophecies: the more pessimistic consumers are, the worse a recession, which, in turn, aggravates the opinions of consumers about the future. To underpin this point, Howrey (2001) reported some predictive power of the CCI for the probability of a recession. Moreover, the desire of private households to have a buffer stock of savings can justify an impact of consumer confidence. A fall in confidence caused by higher income uncertainty might lead to an increase in precautionary savings. Consumption is forced to decline as consumers plan to rebuild their stock of assets (see Caroll *et al.*, 1994). Provided that habit formation prevents consumption from adjusting fully and instantaneously, consumption expenditures are reduced for some time.

MEASURING CONSUMER CONFIDENCE

As it is a psychological concept, consumer confidence is difficult to measure. In collaboration with national partners and institutions, the European Commission (2007) conducts a harmonized survey of private households to collect the opinions of consumers in each EU member state regarding past, current, and future developments. Overall, 23,000 euro area households participate in the survey. Results are obtained for individual countries. The survey is done monthly and comprises 12 questions (11 for the euro area), which are organized around four topics: financial situation of the household, general economic situation, savings, and intentions with respect to major purchases. The questionnaire is included in the Appendix. A five-option ordinal scale is the rule for the answer scheme (conditions are or will get a lot better, better, the same, worse, a lot worse). Answers are aggregated as balances of positive over negative results per question, where extreme answers receive double weights. Euro area series are constructed as a weighted average of the aggregate country replies, where weights reflect the country's share in area-wide private consumption at constant prices.

The balanced series are used to construct a composite indicator for the euro area. The CCI is based on the balances of four forward-looking questions in the survey: expected change in financial situation, expected change in general economic situation, expected change in unemployment, and expected change in savings. Expectations refer to the period 12 months ahead. Neither questions related to the past and the current state of the economy, nor price expectations, nor plans of major purchases are included. The CCI is the simple average of the seasonally adjusted balances of answers to the respective questions (Gayer and Genet, 2006). The balanced series are not standardized prior to their aggregation, i.e., the highly volatile series plays a larger role in the overall indicator.

DESIGN OF THE FORECASTING EXERCISE

The delayed release of many time series in the national accounts is a serious impediment in assessing the current state of the economy. However, monthly indicators are readily available and might be exploited to predict the variable under study. The gap between the monthly indicator and the series of national accounts is closed by the so-called bridge equations. In the bridge equations applied in the forecasting exercise, the monthly indicator is aggregated to quarterly averages and used to forecast private consumption growth in the respective quarter. Although this is a coincident indicator by construction, it has actually a lead of 1.5 months because of the publication delay of national accounts.

As an alternative to the bridge equations, monthly information is employed directly to forecast consumption growth using a MIDAS approach (Ghysels *et al.*, 2007). In this setting, private consumption growth is directly related to the consumer confidence measure of a particular month. Three specifications can be compared in the case of quarterly data. Forecasts for consumption are derived with information on consumer confidence for the first, second, and third months within the respective quarter. Thus, it can be examined whether a specific month is useful in making the predictions. Compared to bridge equations, the first two models have a real lead with respect to private consumption growth.

The forecasts exploit different subsets of the survey information. As a preliminary step, the forecasting performance is explored for each of the single questions (Q1–Q12) in the consumer survey. The aim of this exercise is to check whether particular questions have a better forecasting performance than others. Afterwards, combined forecasts are derived. It is well known from many previous studies that the combination of forecasts can increase the accuracy relative to individual predictions; see, for example, Dreger and Schumacher (2005) for leading indicators of the business cycle. One strategy to combine forecasts is to pool all the questions in the consumer survey. As an alternative, the aggregate is constructed on the basis of the best-performing questions. To identify these questions the model confidence set (MCS) suggested by Hansen *et al.* (2005) has been employed. Here, a confidence set is selected from the individual models, which should contain the best-performing model according to some specified level of confidence.

Pooling methods refer to simple averages (SA), principal components (PC), correlation-weighted (CW) and forecast-weighted (FW) averages. In the PC analysis, the first two components represent 70–80% of the overall variance of the individual questions in the consumer survey. As this share increases rather modestly if further factors are considered, only the first two components are extracted (PC1 and PC2). The weights in the CW forecast correspond to the squared maximum correlation coefficients between private consumption growth and the respective question in the consumer survey, while the FW weights are equal to the inverse of the root mean square forecast error of individual questions. Hence, questions with a lower individual forecasting record are downweighted.

OUT-OF-SAMPLE FORECASTING PERFORMANCE

For the MIDAS approach, as well as for the bridge equations, the forecasting exercise is based on the equation

$$\Delta^4 y_t = \alpha + \beta(L)\Delta y_t + \gamma(L)c_t + \varepsilon_t \tag{1}$$

where $\Delta^4 y(\Delta y)$ is the year-on-year (quarter-on-quarter) growth rate of real private consumption, c_t is a confidence measure, and ε_t is a disturbance term that should fulfil the white noise properties. The order of the lag polynomials $\beta(L)$ and $\gamma(L)$ is determined by the Schwarz Bayes information criterion, where the maximum lag length is set to 4. The benchmark is an autoregressive process, with no confidence measures included. Because of the lag structure, it might be also seen as a time series approximation to a fundamental economic model.

The forecasting performance is evaluated in an out-of-sample exercise. This mimics the actual situation the forecaster is confronted with. The forecasts are conducted in a recursive manner. The first estimation subsample is 1996:Q1–2000:Q3 and the forecast subsample is 2000:Q4–2010:Q1. After the first estimation, the forecast for 2000:Q4 is produced. This first forecast is used to obtain the weights for some combination of forecasts and is not accounted for in evaluating the forecasting accuracy. The estimation subsample is then extended by one quarter to 1996:Q1–2000:Q4 and the forecast for 2001:Q1 is made. This process is repeated until the end of the sample (2010:Q4). Hence the forecasting accuracy is evaluated for the period 2001:Q1–2010:Q4, covering 40 quarters. Note that the recent financial crisis is covered by the exercise. However, the results are not critically influenced by this event.

In fact, two specifications have been tried in the estimation exercise: a rolling and an expanding window. Although the rolling window can be useful especially in periods of structural breaks, higher forecasting accuracy is generally obtained for the models with an expanding window. To save space only the results for the expanding estimation window are shown. All results not on display are available from the authors upon request.

The forecast accuracy is evaluated by the root mean squared forecast error (RMSFE) and the mean absolute forecast error (MAFE) criteria. A relative RMSFE (MAFE) is calculated as a ratio of the RMSFE (MAFE) of an alternative to that of the benchmark model. RMSFEs (MAFEs) below 1 points out to a better forecast than the benchmark, while a relative RMSFE (MAFE) larger than 1 indicates a worse forecast. To assess the significance of the results, tests of predictive accuracy are conducted. The Diebold-Mariano (1995) test is used to investigate the null hypothesis that the competing models have an equal forecasting accuracy. Simulation results indicate that the Diebold–Mariano test statistic can be compared to standard normal critical values, as long as the forecasts are generated under rolling or recursive schemes (see Giacomini and White, 2006). A modified version of the Diebold–Mariano test with a small-sample correction to the variance suggested by Harvey *et al.* (1998) is preferred. The test is applied for the RMFSEs and the MAFEs. Moreover, encompassing tests proposed by Harvey *et al.* (1998) are carried out. They are used in order to examine whether the information of one method is already embedded in a competing forecast.

The out-of-sample exercise was conducted for the euro area as well as for its three largest member countries: France, Germany, and Italy. In order to save space we report here only the results concerning the euro area aggregate. The results for the individual countries are available from the authors upon request.

The out-of-sample forecasting results obtained for the single questions are displayed in Table I. The first three columns of the table contain the RMSFE and the relative RMSFE as well as the p-values of the modified Diebold–Mariano test, where the null hypothesis states that the RMSFE of an alternative is equal to that of the benchmark model. Columns 4–6 report MAFE, relative MAFE, and the p-values of the modified Diebold–Mariano test for the equality of the MAFE of the alternative and benchmark models. Column 7 (ENCOMP1) shows the p-values of the encompassing test, whose null hypothesis is that the benchmark encompasses the alternative model. Finally, column ENCOMP2 reports the p-values of the encompassing test, whose null hypothesis states that the alternative encompasses the benchmark model.

The CCI from the European Commission performs better than the autoregressive benchmark for the euro area and France, although the differences are often not significant. Its inclusion actually worsens the forecasting performance for Germany and especially for Italy, where the losses exceed 5%, although the differences are often not significant. This result does not imply that survey information is irrelevant to predict private consumption growth, as it might reflect inappropriate pooling methods.

In fact, the MIDAS forecasts become more precise if the prediction is based on the data available in the later months within a quarter. Looking at the second question, for example, the average RMSFE in the first month is 0.334, compared to 0.319 in the second and 0.310 in the third. Therefore, the forecasting power is improved by 7% (0.310/0.334) within a quarter, if the later data are used. The bridge equation produces an intermediate forecast accuracy (0.320). However, this picture is not robust. For questions Q6–Q8 (inflation, unemployment, major purchases), the errors are constant, or become larger, if forecasts are based on data for subsequent months. Here, the best alternative refers to the forecast based on the first-month observation. In other words, survey information related to inflation, unemployment, and major purchases has better leading properties.

Questions Q2 (expected change in the financial situation) and Q4 (expected general economic situation) are able to outperform the benchmark consistently. For example, the gain in terms of forecasting accuracy is about 10% if the growth rate of private consumption is predicted on grounds of Q2. All other individual questions produce similar or even larger forecast errors than the CCI.

The results for the euro area do not generalize to individual countries. This may be due to an aggregation effect, as idiosyncratic fluctuations are removed at the euro area level. For example, Q2 (expected change in the financial situation), Q4 (expected general economic situation), and Q8 (major purchases) are useful for predicting the change in private consumption only in France. The forecasting gain is about 10% relative to the benchmark. However, single questions are unable to outperform the benchmark in Germany and Italy. These findings correspond to differences in the short-run dynamics of private consumption that can be found across euro area member states (Dreger and Reimers, 2009).

Next, combinations of forecasts are considered (Table II). In this exercise, the principal components are calculated at each step of the iterations. Similarly, the weights for the composite indicators CW and the FW are continuously updated, and the MCS is revised each round.[1] This implies that the set of best-performing questions selected by the MCS approach may change during the iterations. Nonetheless, all the settings utilize only the information available at the time the forecast is made. The results of the selection exercise are exhibited in Figure 1. It depicts the relative

[1] The MCS test has been carried out using the MulCom package for Ox written by Hansen and Lunde. The confidence level is set to 50%, the block-length parameter, d, is equal to 2, and the number of bootstrap resamples is 10,000.

Table I. Out-of-sample performance of individual questions in the consumer survey, euro area

	RMSFE	Relative	p-value	MAFE	Relative	p-value	ENCOMP1	ENCOMP2
Bridge equation								
AR	0.354	1.000		0.287	1.000			
CCI	0.334	0.942	0.094	0.268	0.934	0.102	0.014	0.915
Q1	0.354	0.998	0.489	0.283	0.987	0.425	0.287	0.343
Q2	0.320	0.902	0.114	0.248	0.865	0.072	0.016	0.508
Q3	0.354	0.998	0.483	0.286	0.997	0.478	0.193	0.238
Q4	0.312	0.879	0.047	0.249	0.867	0.048	0.001	0.786
Q5	0.358	1.010	0.537	0.278	0.970	0.390	0.061	0.094
Q6	0.352	0.993	0.458	0.272	0.948	0.210	0.268	0.420
Q7	0.363	1.025	0.763	0.292	1.018	0.673	0.926	0.133
Q8	0.354	0.998	0.491	0.268	0.934	0.254	0.108	0.213
Q9	0.341	0.963	0.330	0.280	0.975	0.400	0.008	0.196
Q10	0.379	1.069	0.927	0.301	1.049	0.879	0.273	0.091
Q11	0.351	0.992	0.456	0.277	0.966	0.327	0.193	0.219
Q12	0.389	1.097	0.957	0.311	1.083	0.976	0.095	0.081
MIDAS 1								
AR	0.354	1.000		0.287	1.000			
CCI	0.348	0.982	0.304	0.278	0.968	0.231	0.096	0.645
Q1	0.359	1.014	0.590	0.286	0.997	0.485	0.400	0.326
Q2	0.334	0.943	0.228	0.255	0.889	0.107	0.038	0.433
Q3	0.362	1.021	0.670	0.294	1.024	0.658	0.428	0.196
Q4	0.323	0.912	0.062	0.263	0.918	0.125	0.002	0.693
Q5	0.353	0.996	0.485	0.277	0.965	0.373	0.031	0.090
Q6	0.342	0.966	0.284	0.263	0.917	0.095	0.118	0.653
Q7	0.367	1.036	0.881	0.292	1.017	0.679	0.623	0.074
Q8	0.355	1.003	0.517	0.274	0.954	0.307	0.142	0.154
Q9	0.344	0.971	0.315	0.275	0.959	0.301	0.005	0.335
Q10	0.376	1.061	0.964	0.299	1.041	0.897	0.133	0.043
Q11	0.373	1.051	0.717	0.288	1.005	0.522	0.530	0.245
Q12	0.378	1.068	0.972	0.305	1.064	0.961	0.081	0.049
MIDAS 2								
AR	0.354	1.000		0.287	1.000			
CCI	0.338	0.953	0.122	0.270	0.943	0.119	0.022	0.982
Q1	0.356	1.006	0.543	0.287	1.000	0.499	0.386	0.353
Q2	0.319	0.900	0.089	0.249	0.866	0.057	0.012	0.817
Q3	0.353	0.998	0.481	0.286	0.996	0.472	0.182	0.205
Q4	0.322	0.909	0.073	0.257	0.895	0.070	0.003	0.759
Q5	0.362	1.021	0.576	0.281	0.980	0.427	0.065	0.070
Q6	0.360	1.016	0.590	0.280	0.975	0.348	0.390	0.254
Q7	0.363	1.025	0.763	0.292	1.018	0.683	0.931	0.132
Q8	0.352	0.993	0.469	0.267	0.932	0.228	0.122	0.296
Q9	0.341	0.963	0.299	0.285	0.994	0.470	0.020	0.198
Q10	0.373	1.054	0.902	0.296	1.032	0.790	0.381	0.109
Q11	0.341	0.964	0.296	0.269	0.937	0.204	0.118	0.391
Q12	0.386	1.090	0.965	0.309	1.078	0.983	0.074	0.070
MIDAS 3								
AR	0.354	1.000		0.287	1.000			
CCI	0.320	0.904	0.054	0.257	0.896	0.063	0.006	0.866
Q1	0.346	0.976	0.356	0.278	0.969	0.331	0.178	0.420
Q2	0.310	0.874	0.084	0.245	0.854	0.075	0.011	0.535
Q3	0.346	0.975	0.296	0.280	0.975	0.336	0.087	0.389
Q4	0.305	0.861	0.065	0.237	0.828	0.039	0.002	0.588
Q5	0.358	1.011	0.548	0.278	0.968	0.373	0.112	0.126
Q6	0.356	1.006	0.539	0.282	0.984	0.392	0.433	0.394
Q7	0.358	1.010	0.601	0.289	1.007	0.563	0.524	0.240
Q8	0.351	0.991	0.469	0.268	0.934	0.267	0.095	0.218
Q9	0.347	0.980	0.411	0.296	1.030	0.628	0.021	0.183
Q10	0.375	1.058	0.917	0.300	1.044	0.882	0.286	0.105
Q11	0.337	0.950	0.242	0.263	0.915	0.151	0.081	0.453
Q12	0.390	1.100	0.939	0.310	1.081	0.968	0.125	0.122

Note: For the design of the out-of-sample forecasting exercise, see the discussion in the text. The forecasting period is 2001:Q1–2010:Q4. Entries show the RMSFE (first column), the relative RMFSE (second column), MAFE (third column), and relative MAFE (fourth column) for the MIDAS and bridge equations The relative RMSFE (MAFE) is the ratio of the RMSFE (MAFE) of a particular forecast to the RMSFE (MAFE) of the autoregressive benchmark.

Table II. Out-of-sample performance of combined questions in the consumer survey, euro area

	RMSFE	Relative	*p*-value	MAFE	Relative	*p*-value	ENCOMP1	ENCOMP2
Bridge equation								
CCI	0.334	0.942	0.094	0.268	0.934	0.102	0.014	0.915
PC1	0.337	0.951	0.170	0.269	0.939	0.156	0.038	0.865
PC2	0.354	1.000	0.502	0.285	0.994	0.475	0.054	0.095
SA	0.326	0.920	0.013	0.261	0.912	0.014	0.004	0.127
CW	0.325	0.918	0.043	0.260	0.906	0.038	0.011	0.454
FW	0.338	0.954	0.149	0.268	0.934	0.064	0.087	0.707
SA_MCS	0.347	0.978	0.365	0.271	0.946	0.190	0.190	0.632
CW_MCS	0.301	0.849	0.007	0.237	0.827	0.005	0.005	0.153
FW_MCS	0.301	0.849	0.004	0.239	0.833	0.003	0.005	0.052
MIDAS 1								
CCI	0.348	0.982	0.304	0.278	0.968	0.231	0.096	0.645
PC1	0.347	0.980	0.357	0.277	0.966	0.292	0.115	0.562
PC2	0.356	1.006	0.520	0.277	0.966	0.378	0.022	0.078
SA	0.334	0.943	0.033	0.268	0.934	0.047	0.008	0.315
CW	0.334	0.943	0.095	0.267	0.931	0.085	0.019	0.740
FW	0.344	0.972	0.213	0.274	0.956	0.145	0.104	0.961
SA_MCS	0.359	1.014	0.589	0.283	0.986	0.421	0.341	0.277
CW_MCS	0.300	0.847	0.002	0.233	0.814	0.004	0.001	0.120
FW_MCS	0.300	0.847	0.001	0.233	0.812	0.002	0.002	0.044
MIDAS 2								
CCI	0.338	0.953	0.122	0.270	0.943	0.119	0.022	0.982
PC1	0.337	0.952	0.158	0.270	0.943	0.152	0.031	0.918
PC2	0.363	1.025	0.600	0.286	0.997	0.489	0.069	0.048
SA	0.329	0.927	0.011	0.263	0.916	0.010	0.004	0.099
CW	0.328	0.926	0.040	0.263	0.917	0.038	0.012	0.394
FW	0.348	0.982	0.374	0.273	0.951	0.147	0.309	0.814
SA_MCS	0.349	0.984	0.399	0.274	0.955	0.203	0.286	0.714
CW_MCS	0.315	0.889	0.012	0.251	0.877	0.012	0.009	0.151
FW_MCS	0.312	0.881	0.004	0.249	0.868	0.004	0.006	0.035
MIDAS 3								
CCI	0.320	0.904	0.054	0.257	0.896	0.063	0.006	0.866
PC1	0.325	0.918	0.082	0.261	0.909	0.089	0.016	0.927
PC2	0.357	1.009	0.536	0.284	0.990	0.461	0.144	0.132
SA	0.322	0.909	0.016	0.261	0.908	0.017	0.008	0.133
CW	0.321	0.906	0.037	0.258	0.901	0.034	0.014	0.356
FW	0.333	0.941	0.097	0.268	0.934	0.060	0.064	0.498
SA_MCS	0.332	0.936	0.142	0.262	0.913	0.043	0.060	0.826
CW_MCS	0.332	0.937	0.163	0.260	0.906	0.059	0.069	0.936
FW_MCS	0.334	0.943	0.157	0.266	0.926	0.065	0.088	0.747

Note: The forecasting period is 2001:Q1–2010:Q4. Entries show the RMSFE (first column), the relative RMFSE (second column), MAFE (third column), and relative MAFE (fourth column) for the MIDAS and bridge equations. The relative RMSFE (MAFE) is the ratio of the RMSFE (MAFE) of a particular forecast to the RMSFE (MAFE) of the CCI reported by the European Commission. SA is the simple average of forecasts; PC is the forecast based on the principal components; CW, FW are the model combinations with weights based on correlation or on the forecast errors, respectively, MCS is the model combination based on the model confidence set.

frequencies with which each question is selected into the MCS. Thus, the graphs show the questions that are particularly relevant to forecast private consumption.

The forecasting performance of the composite indicators is not markedly superior compared to the benchmark, when the aggregate is constructed from all the questions in the consumer survey, i.e., no pre-selection is applied. Although the combined forecasts are able to outperform the benchmark, the gains are usually small and not significant. However, the picture improves if the questions are filtered by the pre-selection process (MCS). If the composite indicator is based only on the best-performing questions, the increase in the forecasting accuracy is notable, provided that the weights are determined by a data-driven approach. The gains are often significant for the euro area (15% improvement with respect to the autoregressive benchmark), France (21%) and Italy (12%). The forecast for Germany can be also improved by 12%, but is significant only in a few cases. Finally, the encompassing tests indicate that the null hypothesis, according to which the alternative specification is already embedded in the benchmark, is rejected rather often. Thus, the indicator models provide additional information not yet included in the benchmark. In contrast,

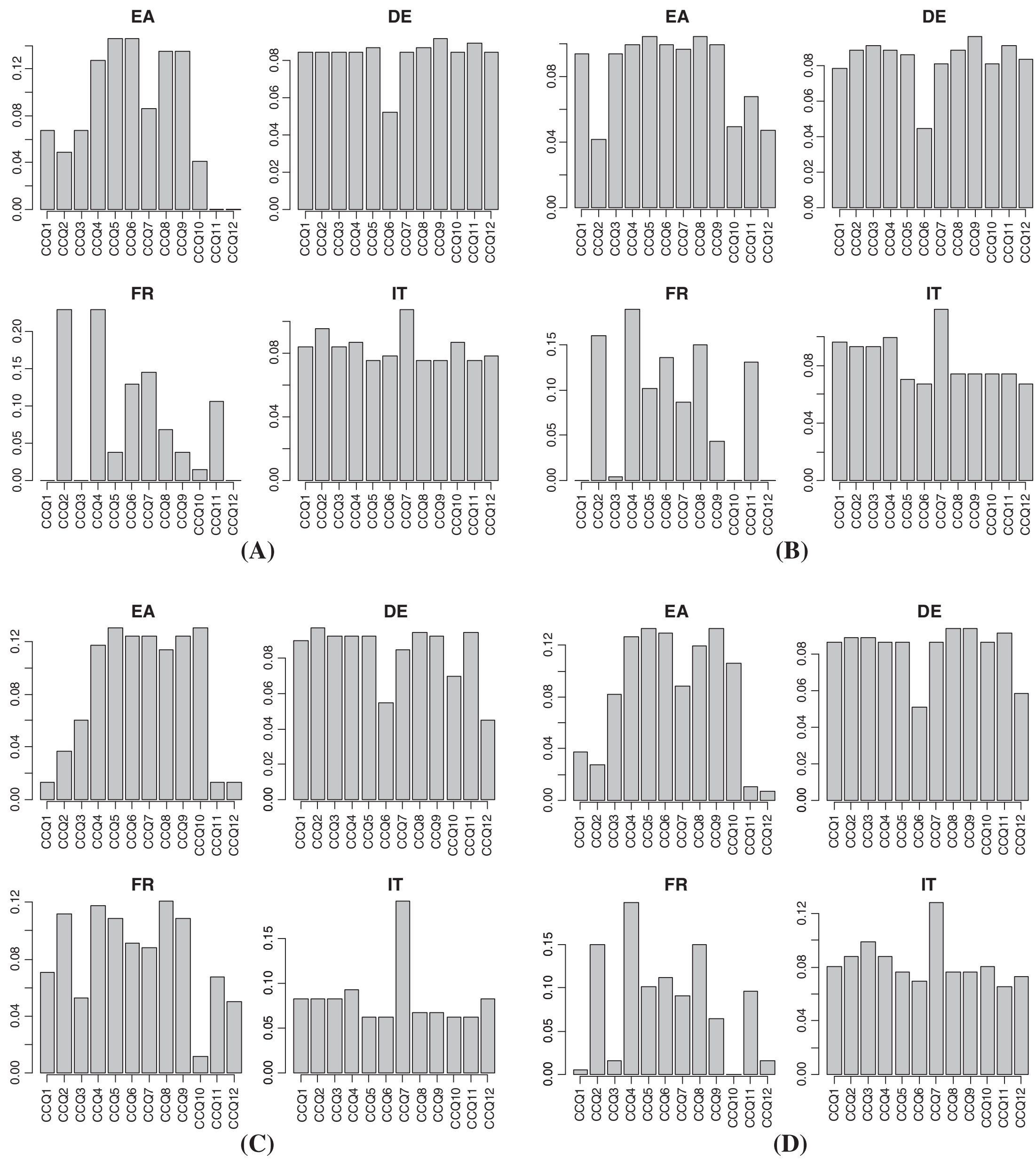

Figure 1. Frequency of selected questions. (A) First month MIDAS equation. (B) Second month MIDAS equation. (C) Third month MIDAS equation. (D) Bridge equation. *Note*: Pre-selection of questions according to the model confidence set suggested by Hansen *et al.* (2005). Selections are made each round of the forecasting exercise

the null hypothesis is usually accepted if the test is specified in the reversed direction. Therefore, the autoregressive benchmark does not improve the accuracy of the indicator forecast.

CONCLUSION

Survey-based indicators, such as consumer confidence, are widely seen as leading indicators for economic activity, especially for the future development of private consumption expenditures. Although they receive high attention in the mass media, their forecasting power appears to be very limited. This paper takes a fresh look at the survey data in the CCI reported by the European Commission for the euro area and individual EU countries. A MIDAS approach is applied and compared to the outcome of bridge equations. The analysis shows that the forecasting performance could be increased. The gains are particularly visible for the euro area, France, and Italy. The forecast for Germany can be significantly improved in a few cases. The result does not mean that reasonable forecasts for private consumption can be derived from the survey information alone. It only implies that the CCI can be improved, if the survey data are exploited in a more appropriate way. Overall, the composite indicator should be built upon pre-selection methods, while data-driven aggregation methods should be applied to determine the weights of the individual ingredients.

APPENDIX: QUESTIONNAIRE FOR CONSUMER SURVEY

Q1: How has the financial situation of your household changed over the last 12 months?
Q2: How do you expect the financial position of your household to change over the next 12 months?
Q3: How do you think the general economic situation in the country has changed over the past 12 months?
Q4: How do you expect the general economic situation in this country to develop over the next 12 months?
Q5: How do you think that consumer prices have developed over the last 12 months?
Q6: By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months?
Q7: How do you expect the number of people unemployed in this country to change over the next 12 months?
Q8: In view of the general economic situation, do you think that now it is the right moment for people to make major purchases such as furniture, electrical/electronic devices, etc.?
Q9: Compared to the past 12 months, do you expect to spend more or less money on major purchases (furniture, electrical/electronic devices, etc.) over the next 12 months?
Q10: In view of the general economic situation, how are the conditions to save?
Q11: Over the next 12 months, how likely is it that you save any money?
Q12: Given the current financial situation of your household, how much do you save?

See European Commission (2007). The actual consumer confidence indicator is based on questions Q2, Q4, Q7 and Q11.

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