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Abstract

This paper examines whether the disaggregation of consumer sentiment data into its sub-components improves the real-time capacity to forecast GDP and consumption. A Bayesian error correction approach augmented with the consumer sentiment index and permutations of the consumer sentiment sub-indexes is used to evaluate forecasting power. The forecasts are benchmarked against both composite forecasts and forecasts from standard error correction models. Using Australian data, we find that consumer sentiment data increases the accuracy of GDP and consumption forecasts, with certain components of consumer sentiment consistently providing better forecasts than aggregate consumer sentiment data.

Keywords: Bayesian; Composite forecast; Consumer sentiment; Cointegration.

JEL classification: E27; C32; C11

1 Introduction

A question of concern from a forecasting perspective is whether consumer sentiment provides leading information in forecasting household consumption and, in turn, GDP. A number of international studies have provided evidence in this regard. Souleles (2004) and Carroll et al. (1994) show that the Michigan Index of Consumer Sentiment assists in forecasting consumption for the United States. Acemoglu and Scott (1994) use United Kingdom consumer sentiment data to arrive at a similar conclusion for the UK. Utaka (2003) also shows a significant association between Japanese consumer sentiment and Japan's GDP. Using Australian data, this paper expands on the existing literature by considering whether the disaggregation of consumer sentiment into its sub-components improves the capacity to forecast GDP and consumption.

There are two major motivations for using disaggregated consumer sentiment data to forecast GDP and consumption. First, consumer sentiment indices are typically obtained as a weighted average of subindexes focusing on particular aspects of consumer sentiment. The subindexes are constructed by reference to consumer responses regarding family finances, economic conditions and purchasing intentions over various time horizons. The varying scope and time horizon of the subindexes may well be exploitable for forecasting purposes. Relative to aggregate consumer sentiment, the subindexes concerning present conditions and intentions may improve short-term forecasts (with an analogous interpretation for subindexes concerning longer term conditions and intentions). In turn, it may reasonably be expected that subindexes pertaining to family finances will provide better forecasts of consumption and production than subindexes concerning the more amorphous and difficult task of judging economic conditions. Second, the substantial contribution of consumption to the GDP figure, and associated evidence of a cointegrating relationship between GDP and consumption, raises the possibility that consumer sentiment is a useful predictor of both variables.

In contrast to findings on the leading relationship between consumer sentiment and GDP obtained using in-sample methods, we examine the real time predictive power of consumer sentiment data for GDP and consumption. We, therefore, avoid the in-sample potential for detecting a spurious source of predictability (Ashley, Granger and Schmalensee,1980). The forecasts are constructed in a Bayesian context, and we evaluate the performance of individual model forecasts against their composite equivalents, as well as the forecasting impact of tight and loose Minnesota priors. Given the possibility of a significant cointegrating relationship between GDP and consumption, we model the association between the two variables using a Bayesian error correction model (BECM). The consumer sentiment index and its individual components are introduced into the BECM as independent variables. An incentive for using a Bayesian ECM assess the incremental forecasting capacity of consumer sentiment data is that prior information is used to reduce the possibility of producing erratic forecasts and, in conjunction with the forecast horizon, to emphasize the short or long run dynamics of the model[1] (LeSage, 1990).

In the next section, we review the consumer sentiment, GDP and consumption data used in this paper. Section 3 defines the BECM used in this paper and the approach adopted for incorporating consumer sentiment data into the model. Section 4 presents our method of generating composite forecasts. The results and their implications are discussed in Section 5, while Section 6 concludes the paper.

2 Consumer Sentiment Data

Consumer sentiment data are obtained monthly using the Westpac-Melbourne Institute Consumer Sentiment Index and its subindexes. Survey results are available seven days after the survey period and the full set of data for each quarter is available prior to the official release of the National Accounts (containing GDP and consumption data) by the Australia Bureau of Statistics. The Survey is structured along the lines of the University of Michigan Index of Consumer Sentiment and it's five subindexes are constructed by reference to responses concerning: 1) current family finances, 2) family finances in the next twelve months, 3) short-term economic conditions (i.e., in the next twelve months), 4) medium-term economic conditions (i.e., in the next five years), and 5) present conditions for purchasing goods or services. The consumer sentiment is computed as the simple average of

[1] Lin and Tsay (1996) also suggest that accounting for cointegration between variables improves forecasts.

the five subindexes. Survey responses are also used to construct two additional subindexes, the current condition index and the consumer expectations index.

2.1 The Association Between Australian GDP and Consumption

Since 1959, consumption has accounted for approximately 60 per cent of GDP on average. Not surprisingly, both GDP and consumption levels share a similar path. Johansen's trace test (using an ECM with one to six lags) is used to examine whether the two variables are cointegrated. The trace statistics, presented in Table 1, indicate that GDP and consumption are cointegrated at all six lags. Table 1 also presents the results of Augmented Dickey-Fuller and Phillips-Perron unit root tests suggesting that both GDP and consumption are I(1) variables.

Table 1: Test for cointegration and unit roots

	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	95% Critical value
			Trace Statistics				
Rank 0	17.04	15.54	20.85	19.65	22.35	16.95	15.49
Rank 1	1.15	1.72	1.91	2.47	3.26	3.58	3.84
			Augmented Dickey-Fuller				
GDP	-1.13	-1.35	-1.39	-1.86	-2.05	-2.07	-2.88
Consumption	-1.09	-1.42	-1.85	-1.97	-2.09	-2.01	-2.88
			Phillips-Perron				
GDP	-1.04	-1.04	-1.02	-1.03	-1.04	-1.03	-2.88
Consumption	-1.16	-1.15	-1.13	-1.11	-1.11	-1.10	-2.88

3 A Bayesian ECM Incorporating the Consumer Sentiment Index and its subindexes

A BECM augmented with consumer sentiment data is used to produce forecasts of GDP and consumption contingent on the cointegration observed between the two variables[2]. To ensure that the frequency of GDP and consumption matches that of the consumer sentiment data, the monthly consumer sentiment indexes are converted into three quarterly indexes. Each quarterly index takes on the value associated with a particular month in the quarter. For ease of exposition, the quarterly indexes are denoted as $CSI_t^{(k)}, CI_t^{(k)}, EI_t^{(k)}$ and $SI_{it}^{(k)}$ $(i = 1, ..., 5)$, where the superscript k indicates the $k - th$ month in the quarter ($k = 1$ for the first month, $k = 2$ for the second month and $k = 3$ for the third month). $CSI_t^{(k)}$ is the consumer sentiment index, $CI_t^{(k)}$ is the current condition index, $EI_t^{(k)}$ is the consumer expectations index, and $SI_{it}^{(k)}$ is the $i-th$ consumer sentiment subindex.

The error correction model with $CSI_t^{(k)}, CI_t^{(k)}, EI_t^{(k)}, SI_{it}^{(k)}$ as exogenous variables take the following form:

$$\triangle Y_t = c + \alpha\beta Y_{t-1} + \sum_{i=1}^{p} B_i \triangle Y_{t-i} + \gamma X_{t-q}^{(k)} + e_t, \qquad k = 1, 2, 3 \tag{1}$$

where Y_t is a (2×1) vector of the GDP and consumption variables at t, $X_t^{(k)}$ is a (1×8) matrix such that $X_{t-q}^{(k)} = [CSI_{t-q}^{(k)} \;\; CI_{t-q}^{(k)} \;\; EI_{t-q}^{(k)} \;\; SI_{1t-q}^{(k)} \;\; SI_{2t-q}^{(k)} \;\; SI_{3t-q}^{(k)} \;\; SI_{4t-q}^{(k)} \;\; SI_{5t-q}^{(k)}]'$, α, β and γ are (1×2), (2×2) and (2×8) matrices, respectively, of unknown parameters, and $e_t \sim N(0, \Sigma)$. In this paper, we allow the indexes to influence the GDP and consumption up to four quarters ahead (i.e., $q = 0, 1, 2$ and 3). The number of forecast steps for Y_t also depends on q. For instance, given $q = 0$ a single forecast for time t is produced whereas $q = 3$ allows for four forecasts (for times t up to $t + 3$).

To allow for alternative permutations of the indexes, γ is decomposed into

$$\gamma = \begin{bmatrix} \delta_1' F \\ \delta_2' F \end{bmatrix}, \tag{2}$$

where F is an (8×8) diagonal restriction matrix and δ_1, δ_2 are (8×1) vectors related to the first and second equations respectively. To restrict the model to $SI_{1t}^{(k)}$ and

[2] Shoesmith (1995) finds that the short and long term forecasts from the BECM outperform those from BVAR and VAR models while Chow and Choy (2006) find that the BVAR performs better than the BECM in forecasting the global electronics cycle. Amisano and Serati (1999) advocate the use of the Bayesian variant of the ECM on the basis that it allows for the super-consistent estimation of the model's long-run parameters.

$SI_{2t}^{(k)}$, for example, we set $F = diag\left(\left[\begin{array}{cccccccc} 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 \end{array}\right]\right)$. Since $CSI_t^{(k)}$ is a linear function of $CI_t^{(k)}$ and $EI_t^{(k)}$, and $CI_t^{(k)}$ and $EI_t^{(k)}$ are linear functions of $SI_{it}^{(k)}$, $i = 1, ..., 5$, we do not allow any interaction between $CSI_t^{(k)}$ and ($CI_t^{(k)}$, $EI_t^{(k)}$, $SI_{it}^{(k)}$) or between ($CI_t^{(k)}$, $EI_t^{(k)}$) and $SI_{it}^{(k)}$. All in all, for each k there are 35 possible permutations for $X_{t+q}^{(k)}$ (31 stemming from $SI_{it}^{(k)}$, 3 stemming from $CI_t^{(k)}$ and $EI_t^{(k)}$, and 1 stemming from $CSI_t^{(k)}$).

This paper follows LeSage (1990) in introducing a Minnesota prior into the ECM.[3] The prior adopts an a priori random walk forecasting framework and may be used to place emphasis on the short-run dynamics of the model or its long-run equilibrium. Two different sets of priors are considered; a tight prior and a loose prior. The tight prior tends to emphasize the model's long-run equilibrium, while the loose prior tends to reduce the role of the error correction term in favour of the model's short-run dynamics (LeSage, 1990). The Minnesota prior is placed on B_i and c while diffuse priors are used for α and γ.

We have assumed that the tight Minnesota prior for equation i uses an overall tightness parameter of 0.1, a harmonic lag decay of 1, a weight of 0.1 for lags of variable i, and symmetric weights of 0.1 for lags of other variables. The loose Minnesota prior for equation i uses an overall tightness parameter of 1, a harmonic lag decay of 1, a weight of 2 for lags of variable i, and symmetric weights of 0.5 for lags of other variables.

A separate model (and forecast) is constructed depending on the prior adopted, the particular permutation of $X_{t-q}^{(k)}$, and the values of q and p ($p = 1$ through to $p = 6$ are considered). Models are also estimated without $X_{t-q}^{(k)}$. In total, 5052 models are considered. Because the value q determines the number of forecast steps, not all models will produce an identical number of forecasts. The number of comparable models at each forecast step declines as q increases. Consequently, there are 5052 comparable models for 1-step ahead forecasts, 3792 models for 2-step ahead forecasts, 2532 models for 3-step ahead forecasts and 1272 models for 4-step ahead forecasts.

[3]Also known as the Litterman prior. See Litterman (1986) for in-depth discussion.

4 The Construction of Composite Forecasts

The forecasting literature tends to find that combining forecasts derived from different models produces better forecasts, on average, than a forecast from a single model (Clemen, 1989; Armstrong, 2001; Palm and Zellner, 2006). To derive composite forecasts we follow Winkler (1981) in generating composite forecasts by combining model-based forecasts and judgment-based priors. Pursuant to Winkler (1981), the forecast errors from the range of models considered at time t are assumed to be normally distributed with zero mean and covariance Σ_{it} such that,

$$\widehat{y}_{it} \sim N(y_{it}u, \Sigma_{it}) \tag{3}$$

where $i = 1$ or 2 denotes GDP or consumption respectively. $\widehat{y}_{it}$ is a vector containing forecasts of y_{it} and u is a vector of ones equal in length to $\widehat{y}_{it}$. Because the estimate of Σ_{it} is computed from the realised forecast errors, the generated weights are influenced by both the forecast precision of the models and any dependencies between the models. The dependencies sometimes result in negative weights. We found, however, that restricting weights to the positive range had little effect on the composite forecasts.

The judgmental component of the composite forecast is introduced in the form of priors on y_{it} and Σ_{it}. The prior for y_{it} is assumed to be uniformly distributed

$$y_{it} \sim U(a, b) \tag{4}$$

whereas an inverted Wishart prior is used for Σ_{it}

$$\Sigma_{it} \sim IW(\Sigma_{i0}, v). \tag{5}$$

The composite forecast is, therefore, given by

$$E(y_{it}|\widehat{y}_{it}) = w'_{it}\widehat{y}_{it} \tag{6}$$

where $\widehat{y}_{it} = [\ y_{i1t} \quad y_{i2t} \quad \ldots \quad y_{iJt}\ ]'$ is a $(J \times 1)$ vector of J forecasts and $w_{it} =$

$[\; w_{i1t} \quad w_{i2t} \quad ... \quad w_{iJt} \;]'$ is a $(J \times 1)$ vector of weights computed using

$$w_{it} = \frac{u'\widetilde{\Sigma}_{it}^{-1}}{u'\widetilde{\Sigma}_{it}^{-1}u}. \tag{7}$$

$\widetilde{\Sigma}_{it}$ is the posterior estimate of Σ_{it} which is given by

$$\widetilde{\Sigma}_{it} = \frac{v}{t+v}\Sigma_{i0} + \frac{t}{t+v}\widehat{\Sigma}_{it} \tag{8}$$

where $\widehat{\Sigma}_{it}$ is computed from the realized forecast errors and $v \geq J$ is a degree of freedom parameter used to calibrate the weight attached to Σ_{i0} when determining $\widetilde{\Sigma}_{it}$.

Σ_{i0} is assumed to be

$$\Sigma_{i0} = \sigma_{i0}^2 \begin{bmatrix} 1 & \rho & \cdots & \rho \\ \rho & 1 & \cdots & \rho \\ \vdots & & \ddots & \vdots \\ \rho & \cdots & \rho & 1 \end{bmatrix} \tag{9}$$

where ρ is a positive number. This assumption is intuitive as the forecasts from competing models are likely to positive correlated. A relatively diffuse prior of $\rho = 0.5$ is used, whereas σ_{i0}^2 is set to the variance of $\triangle y_{it}$ and v is set to J. Finally, the uniform prior for y_{it} is restricted to an upper bound growth of 8% per annum and a lower bound growth of -5% per annum. The large bound renders the prior fairly uninformative and all year-end growth rates prior to 1994:3 lie within this bound.

Although Winkler's (1981) approach is intuitive, a drawback is that the maximum number of models that can be used to produce the composite forecast is limited by the number of time periods for which the realized forecast errors used to estimate $\widehat{\Sigma}_{it}$ are available (otherwise the number of models N exceeds the number of time periods for which realized forecast errors are available T such that $\widehat{\Sigma}_{it}$ is singular). To avoid singularity in $\widehat{\Sigma}_{it}$, the composite forecasts are produced by selecting the best J forecasts by reference to the absolute forecast errors for the immediately preceding period.[4]

5 Results

To evaluate the forecast performance of the models, the sample is divided into two periods. The first period, from 1975:1 (depending on the number of lags) to 1994:2, is used for initial estimation. The second period spanning 1994:3 through to 2007:2 is used to evaluate forecasting accuracy.

The forecast procedure is as follows. The fist period is used to estimate c, α, β, B_i and γ and generate $(q+1)$-step ahead forecasts together with the associated forecasting errors. Next, an additional period of observations is added to the first period before re-estimating the models and generating another $(q+1)$-step ahead forecasts and forecast errors. This recursive procedure continues until 2007:2. The mean absolute percentage errors (MAPE) are used to evaluate the forecasting accuracy of the models.

As mentioned in Section 4, the number of models that can be used to produce the composite forecasts are limited by the number of periods used to generate $\widetilde{\Sigma}_{it}$. Consequently, to ensure that composite forecasts are produced for the same time period as the forecasts from the individual models, we commence computing individual model forecasts ten periods prior to 1994:2. These additional forecasts are only used to estimate $\widetilde{\Sigma}_{it}$ and do not enter into the MAPE calculation. The composite forecasts at 1994:3 are, therefore, produced as the weighted average of the forecasts arising from the ten best forecasting models for the preceding period. In the subsequent period 1994:4, the best ten plus one models are used to estimate $\widetilde{\Sigma}_{it}$ and so on. In total, 62 models are used to produce the final composite forecasts for 2007:2.

Given the large number of models considered in this paper, only a subset of the results is presented.[5] Tables 2 and 3 present the ten lowest MAPE results for the models incorporating the consumer sentiment data (Table 2 is based on

[4] The mean square forecast error criterion was also used to compute the composite forecasts. The results, however, were less accurate than their counterparts based on the absolute forecast error criterion.

[5] The remaining results can be obtained from the corresponding author.

the tight prior whereas Table 3 pertains to the loose prior). Table 4 presents results from a standard BECM without reliance on consumer sentiment data, while Table 5 reports the accuracy of the composite forecasts. Three methods of generating composite forecasts are reported: simple averaging, weighted averaging with weights computed using the inverse of the MSE, and Winkler's (1981) approach.

It is clear that the addition of the consumer sentiment index and its subindexes produces better forecasts of both GDP and consumption than those from a standard BECM. The improved forecast performance is observed irrespective of the adoption of a tight or loose prior, although the forecasts based on the tight prior tend to be better than their loose prior equivalents. Interestingly, forecasts derived from the subindexes clearly outperform those based on the aggregate consumer sentiment index. This suggests that particular subsets of consumer sentiment exhibit a stronger predictive capacity than others.

In this respect, the best five consumption forecasts at the 1-, 2- and 3-step ahead forecast horizons are associated with the subindexes concerning family finances and buying conditions. The medium-term (up to five years) economic conditions subindex, although absent in the best five forecasting models at the shorter forecasting horizons, is present in three of the best five consumption forecasting models at the 4-step ahead horizon. The evidence, therefore, suggests that the best short-term forecasts of consumption rely on shorter-term subindexes concerning family finances and buying conditions, with longer-term sentiment only being relevant for longer-term forecasts. Such a clear interpretation is, however, not available for GDP. The best forecasts for GDP tend to be associated with the subindexes concerning family finances and economic conditions in the next 12 months. In contrast to the evidence for consumption, shorter-term variables consistently provide better forecasts of GDP at all forecast horizons, with the medium-term economic conditions subindex only present in the best GDP forecasting models at the 1-step ahead level. In general, the (shorter-term) subindexes concerning family finances are present in the best forecasting models for both GDP and consumption at all forecast horizons, suggesting that the family finances subset of the consumer sentiment data is most useful for forecasting purposes.

The results also suggest that models incorporating consumer sentiment data for the last month of the quarter (i.e., $X^{(3)}_{t-q}$) provide better shorter term forecasts for both GDP (up to three steps ahead) and consumption (up to two steps ahead). For 4-step ahead forecasts, however, the models incorporating consumer sentiment data in the first month ($k = 1$) for GDP and in the second month ($k = 2$) for consumption appear to provide better forecasts. Consequently, observation of the most recent set of consumer sentiment data predominantly assists in the production of short-term forecasts. In turn, it is evident that, given the application of a tight prior, the models incorporating longer lag lengths (of five or six lags) provide better forecasts for both GDP and consumption. The application of a loose prior, however, noticeably influences the lag length of the preferred GDP forecasting models with two lags (or $p = 2$) clearly providing the best forecasts at the 3- and 4- step ahead horizons. Accordingly the tighter zero prior for lags greater than one (i.e., $i > 1$), which tends to reduce the absolute value of the coefficients at higher lags, appears to better exploit lagged information for GDP forecasting purposes.

In general the inclusion of consumer sentiment data results in a slightly better forecast of consumption than GDP. To some extent, this is expected given the greater theoretical proximity between consumer sentiment and consumption. Overall, the composite forecasts for GDP using Winkler's approach produce better 2-, 3- and 4-step ahead forecasts than all other models including the composite forecasts based on the simple averaging and MSE methods. The accuracy of Winkler's approach does not extend to 1-step ahead forecasts, and the approach is marginally less accurate than the other composite forecasts or the forecasts stemming from the augmented (with consumer sentiment data) BECM (although they tend to be better than the standard BECM forecasts using loose priors). The composite forecasts for consumption, however, are less accurate. Although Winkler's approach produces the best composite forecast (except at the 1-step horizon), the best augmented BECM forecasts outperform their composite forecasts at all steps. The standard BECM models generally produce weaker forecasts than either the augmented BECM models or the composite approach, especially at greater forecast horizons, suggesting that the inclusion of consumer sentiment data produces better forecasts of GDP and consumption.

Table 2. Top 10 BECM forecasts with consumer sentiment data and a tight prior

GDP						Consumption					
Rank	MAPE	Model				Rank	MAPE	Model			
		Combination	p	k	q			Combination	p	k	q
		1-step ahead						1-step ahead			
1	0.4136	11	5	3	0	1	0.3585	1	6	3	0
2	0.4167	3	5	3	0	2	0.3595	1	5	3	0
3	0.4173	2	5	3	0	3	0.3602	17	5	3	0
4	0.4178	11	6	3	0	4	0.3602	17	6	3	0
5	0.4183	10	5	3	0	5	0.3606	5	5	3	0
6	0.4187	10	6	3	0	6	0.3615	5	6	3	0
7	0.4197	2	6	3	0	7	0.3616	21	5	3	0
8	0.4200	18	6	3	0	8	0.3631	25	5	3	0
9	0.4203	3	6	3	0	9	0.3638	25	6	3	0
10	0.4219	18	5	3	0	10	0.3641	9	6	3	0
		2-step ahead						2-step ahead			
1	0.6180	2	6	3	2	1	0.5756	19	4	3	1
2	0.6212	2	5	1	1	2	0.5757	19	2	3	1
3	0.6225	18	6	3	2	3	0.5767	17	2	2	3
4	0.6239	2	5	3	2	4	0.5782	16	4	3	1
5	0.6262	2	6	1	1	5	0.5799	18	2	3	1
6	0.6274	18	5	3	2	6	0.5804	35	2	3	1
7	0.6292	3	5	1	1	7	0.5808	18	4	3	1
8	0.6302	2	5	3	1	8	0.5809	18	2	1	1
9	0.6314	2	6	3	1	9	0.5812	16	4	1	1
10	0.6342	2	2	3	1	10	0.5812	16	6	1	1
		3-step ahead						3-step ahead			
1	0.7769	2	5	3	2	1	0.6625	19	4	2	2
2	0.7781	2	6	3	2	2	0.6684	19	5	2	2
3	0.7816	18	5	3	2	3	0.6716	17	4	2	3
4	0.7832	19	5	3	2	4	0.6748	17	5	2	3
5	0.7848	18	6	3	2	5	0.6774	19	3	2	2
6	0.7878	3	5	3	2	6	0.6872	17	6	2	3
7	0.7908	19	6	1	3	7	0.6888	20	5	1	2
8	0.7934	19	6	3	2	8	0.6906	17	3	2	3
9	0.7984	3	6	3	2	9	0.6918	19	3	3	2
10	0.7999	28	5	3	3	10	0.6923	18	4	3	2
		4-step ahead						4-step ahead			
1	0.9339	19	6	1	3	1	0.7635	20	5	2	3
2	0.9383	23	6	1	3	2	0.7643	29	5	2	3
3	0.9558	23	5	1	3	3	0.7649	29	4	2	3
4	0.9629	19	5	1	3	4	0.7671	28	5	2	3
5	0.9649	21	6	1	3	5	0.7697	21	5	2	3
6	0.9660	19	6	3	3	6	0.7701	25	5	1	3
7	0.9747	28	6	3	3	7	0.7744	24	6	1	3
8	0.9751	19	6	2	3	8	0.7751	24	5	1	3
9	0.9777	17	6	1	3	9	0.7764	28	4	2	3
10	0.9779	28	5	3	3	10	0.7766	28	6	1	3

Refer to the Appendix to identify the thirty-five combinations.

Table 3. Top 10 BECM forecasts with consumer sentiment data and a loose prior

GDP						Consumption					
Rank	MAPE	Model				Rank	MAPE	Model			
		Combination	p	k	q			Combination	p	k	q
1-step ahead						1-step ahead					
1	0.4450	2	5	3	0	1	0.3578	17	5	3	0
2	0.4462	3	5	3	0	2	0.3605	21	5	3	0
3	0.4465	10	5	3	0	3	0.3609	1	5	3	0
4	0.4483	11	1	3	0	4	0.3612	5	5	3	0
5	0.4483	10	1	3	0	5	0.3682	9	5	3	0
6	0.4488	1	6	3	0	6	0.3684	1	4	3	0
7	0.4488	10	5	2	0	7	0.3692	7	5	3	0
8	0.4491	2	1	3	0	8	0.3709	25	5	3	0
9	0.4491	8	1	1	0	9	0.3710	17	4	3	0
10	0.4492	3	5	3	0	10	0.3718	13	5	3	0
2-step ahead						2-step ahead					
1	0.6463	1	2	3	1	1	0.5719	19	2	3	1
2	0.6490	33	1	3	3	2	0.5729	18	2	1	1
3	0.6506	1	2	1	1	3	0.5745	18	2	3	1
4	0.6548	3	3	3	1	4	0.5772	17	2	2	3
5	0.6583	28	2	3	3	5	0.5783	35	2	3	1
6	0.6590	19	6	1	3	6	0.5808	19	2	1	1
7	0.6591	2	3	3	1	7	0.5809	24	2	1	1
8	0.6598	29	2	3	3	8	0.5810	16	2	3	1
9	0.6604	19	2	1	3	9	0.5815	20	2	3	1
10	0.6627	19	2	3	3	10	0.5819	25	2	1	1
3-step ahead						3-step ahead					
1	0.8099	23	2	1	3	1	0.6790	19	3	2	2
2	0.8197	28	2	3	3	2	0.6825	19	4	2	2
3	0.8215	31	2	1	3	3	0.6832	19	2	2	2
4	0.8236	21	2	1	3	4	0.6960	19	2	3	2
5	0.8242	12	2	3	3	5	0.6983	25	4	1	3
6	0.8295	29	2	3	3	6	0.6985	17	2	2	3
7	0.8305	9	2	3	3	7	0.7004	17	4	2	3
8	0.8308	19	2	1	3	8	0.7080	25	4	2	3
9	0.8363	8	2	3	3	9	0.7083	18	3	2	2
10	0.8374	25	2	3	3	10	0.7084	18	4	2	2
4-step ahead						4-step ahead					
1	0.9319	23	2	1	3	1	0.7556	29	4	2	3
2	0.9498	31	2	1	3	2	0.7641	28	5	2	3
3	0.9562	21	2	1	3	3	0.7653	25	4	1	3
4	0.9569	19	2	1	3	4	0.7671	29	5	2	3
5	0.9719	28	2	3	3	5	0.7697	25	4	2	3
6	0.9775	23	2	2	3	6	0.7706	28	4	2	3
7	0.9817	27	2	1	3	7	0.7780	24	5	2	3
8	0.9848	31	2	2	3	8	0.7831	20	5	2	3
9	0.9859	23	3	1	3	9	0.7836	25	5	2	3
10	0.9874	29	2	1	3	10	0.7865	24	4	2	3

Refer to the Appendix to identify the thirty-five combinations.

Table 4. MAPE from the BECM forecasts without consumer sentiment data

	GDP					Consumption			
p	1 step	2 steps	3 steps	4 steps	p	1 step	2 steps	3 steps	4 steps
	Tight					Tight			
1	0.4595	1.1198	1.1627	1.3462	1	0.4260	1.2382	4.1777	3.4561
2	0.4635	0.6749	0.8773	1.0685	2	0.4264	0.6775	0.9254	1.1150
3	0.4593	0.6603	0.8381	1.0034	3	0.4677	0.7332	0.9964	1.1871
4	0.4637	0.7102	0.9473	1.1755	4	0.4401	0.7027	0.9762	1.1869
5	0.4508	0.6986	0.9509	1.1969	5	0.4546	0.7573	1.0606	1.2846
6	0.4501	0.7016	0.9546	1.2004	6	0.4275	0.6821	0.9234	1.1020
	Loose					Loose			
1	0.4721	1.1258	1.3867	1.5522	1	0.4271	1.2393	4.1517	3.3983
2	0.4791	0.6695	0.8375	1.0016	2	0.4331	0.6788	0.9235	1.1088
3	0.4905	0.7022	0.8321	1.0155	3	0.4643	0.7314	0.9789	1.1561
4	0.4967	0.7259	0.9639	1.1760	4	0.4331	0.7414	1.0086	1.2069
5	0.4944	0.7989	1.0772	1.2874	5	0.4523	0.8123	1.1155	1.3540
6	0.4993	0.7988	1.0874	1.2976	6	0.4350	0.7464	0.9875	1.1728

Table 5. MAPE of the combine forecasts

	GDP					Consumption			
	1 step	2 steps	3 steps	4 steps		1 step	2 steps	3 steps	4 steps
SA	0.46649	0.67993	0.88303	1.1322	SA	0.39546	0.62857	0.73163	0.83244
MSE	0.47188	0.67913	0.86392	1.1048	MSE	0.38994	0.62263	0.71806	0.81484
BCC	0.48223	0.60314	0.66532	0.80654	BCC	0.41068	0.6116	0.67118	0.79979

SA - Simple averaging; MSE - mean square error; BCC - Bayesian combination with correlation between models

6 Concluding Remarks

Using a BECM augmented with the consumer sentiment subindexes produces better forecasts of GDP and consumption than a BECM augmented with the aggregate consumer sentiment index. In turn, forecasts from the BECM augmented with either the consumer sentiment subindexes or the aggregate consumer sentiment index are more accurate than those from a standard BECM. We observe that, in contrast to the buying conditions or economic conditions subindexes, the shorter-term subindexes concerning family finances are consistently present in the better forecasting models for either GDP or consumption at all forecasting horizons. Overall, we find that the composite forecasts for GDP provide better medium term forecasts over any model, while composite forecasts for consumption are only superior to the forecasts generated from the BECM models not augmented with the consumer sentiment subindexes.

The forecasting literature of late has focused on the incremental forecasting capacity of introducing regime-switching components to the ECM (Clarida et al, 2003), and the use of predictive densities to better evaluate the forecasting performance of alternative models (Tay and Wallis, 2000; Pesaran and Skouras, 2001). Our future research aims to amalgamate these two fields of research with the scope of better evaluating the forecasting performance of disaggregated consumer sentiment data.

7 Appendix: Permutations of the Consumer Sentiment Data and Its Sub-indexes

Table A1. Types of combination of the consumer sentiment and its sub-indexes

Combination	$CSI_{t-q}^{(k)}$	$CI_{t-q}^{(k)}$	$EI_{t-q}^{(k)}$	$SI_{1t-q}^{(k)}$	$SI_{2t-q}^{(k)}$	$SI_{3t-q}^{(k)}$	$SI_{4t-q}^{(k)}$	$SI_{5t-q}^{(k)}$
1				×				
2					×			
3				×	×			
4						×		
5				×		×		
6					×	×		
7				×	×	×		
8							×	
9				×			×	
10					×		×	
11				×	×		×	
12						×	×	
13				×		×	×	
14					×	×	×	
15				×	×	×	×	
16								×
17				×				×
18					×			×
19				×	×			×
20						×		×
21				×		×		×
22					×	×		×
23				×	×	×		×
24							×	×
25				×			×	×
26					×		×	×
27				×	×		×	×
28						×	×	×
29				×		×	×	×
30					×	×	×	×
31				×	×	×	×	×
32		×						
33		×	×					
34			×					
35	×							

Note: $CSI_{t-q}^{(k)}$ is the aggregate consumer sentiment index, $CI_{t-q}^{(k)}$ is the current condition index, $EI_{t-q}^{(k)}$ is the expectations index, $SI_{1t-q}^{(k)}$ is the index for current family finances relative to 12 months ago, $SI_{2t-q}^{(k)}$ is the index for current family finances relative to the next 12 months, $SI_{3t-q}^{(k)}$ is the index for economic conditions in the next 12 months, $SI_{4t-q}^{(k)}$ is the index for economic conditions in the next 5 years, and $SI_{5t-q}^{(k)}$ is the (major household items) buying conditions index.

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