Business Cycles and the Role of Confidence: Evidence for Europe*

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Abstract

This paper examines whether indicators of consumer and business confidence can predict movements in GDP over the business cycle for four European economies. The empirical methodology used to investigate the properties of the data comprises cross-correlation statistics, implementing an approach developed by den Haan [Journal of Monetary Economics (2000), Vol. 46, pp. 3–30]. The predictive power of confidence indicators is also examined, investigating whether they can predict discrete events, namely economic downturns, and whether they can quantitatively forecast point estimates of economic activity. The results indicate that both consumer and business confidence indicators are procyclical and generally play a significant role in predicting downturns.

I. Introduction

The view that measures of consumer confidence can predict fluctuations in the level of economic activity independently of other leading indicators is a popular one, though how much additional information is contained in these measures compared with other leading indicators is a matter of dispute (see, e.g. Carroll, Fuhrer and Wilcox, 1994;...
Matsusaka and Sbordone, 1995; Eppright, Arguea and Huth, 1998; Bram and Ludvigson, 1998). The possibility that indicators of business confidence also anticipate business cycle activity has been subject to less empirical scrutiny. In the present study, we use measures of both consumer and business confidence to examine their ability to predict business cycle activity over and above existing leading indicators for four European economies. The data we employ in the study provide consistent measures of business and consumer confidence for the four countries and, to our knowledge, have not previously been used to investigate the role of business and consumer expectations in predicting business cycle fluctuations.

In the following section we provide a summary of the current literature, and in section III the data used in the study are described. The cross-sectional properties of the data are investigated based on an approach developed by den Haan (2000), described in section IV. This methodology is advantageous in that the data do not require detrending and so can be implemented regardless of whether variables are stationary or non-stationary. The remainder of the paper then focuses on the main objectives of the paper, namely, investigating whether confidence measures have a role in forecasting. Specifically, we consider whether confidence indicators can predict economic downturns, i.e. discrete turning points in the business cycle. Finally, confidence indicators are employed in vector autoregression (VAR) analysis to assess out-of-sample quantitative point forecasts of GDP growth, in particular, to address whether forecasting errors are significantly reduced by the inclusion of confidence indicators.

The empirical analysis reveals that, across countries, both consumer and business confidence indicators generally have good predictive power in identifying discrete turning points in the business cycle. By way of example, in the UK a 1 percentage point increase in business confidence reduces the probability of an economic downturn by around 4 percentage points, while a 1 percentage point increase in consumer confidence has a similar impact of reducing the probability of an economic downturn by around 3 percentage points.1 It is also worth noting that there is also a role for confidence indicators in reducing the forecasting error associated with quantitative point estimates. A reduction in forecasting error of around 5%, by the inclusion of confidence indicators, is statistically significant for the UK and the Netherlands.

II. Confidence indicators and economic activity

A theoretical rationalization for a causal link between consumer and business confidence on the one hand and fluctuations in the level of economic activity on the other can be found in a range of dynamic general equilibrium models that incorporate, *inter alia*, the subjective views of economic agents. These models give rise to multiple equilibria that are not determined by standard economic fundamentals and

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1These figures are for illustration. Discrete turning points in the business cycle are estimated via a probit model. This is a nonlinear model in which the effects are evaluated at the mean values of the other variables employed in the model.
in which expectations about the future level of output can become self-fulfilling. As a result, a decline in consumer or business confidence can cause a decline in output, *ceteris paribus* (see, e.g. Milgrom and Roberts, 1990; Ball and Romer, 1991; Ng, 1992; Matsusaka and Sbordone, 1995; Farmer, 1999).

An alternative theoretical justification for a causal link is provided by Potter (1999). He suggests that business cycle asymmetries found in postwar US data are inconsistent with the trends of the economy during the Great Depression. Using a rational expectations model, such inconsistencies are examined by considering the role government policy played in influencing confidence. Potter argues that the ‘ineptness’ of government policy during the Great Depression in bringing about a fall in confidence coupled with the success of postwar stabilization policy in raising confidence is a likely explanation for the asymmetries found in the cycle in recent years.

That there exists a class of macroeconomic models in which changes in consumer and/or business confidence can cause changes in the level of economic activity independently of fundamental macroeconomic variables does not, of course, imply that this link is quantitatively significant. In fact, the empirical literature on the impact of confidence on economic activity yields mixed results. Matsusaka and Sbordone (1995), examining trends in US output over the period 1953–1988, find that consumer sentiment Granger-causes GNP fluctuations, even after controlling for the impact of changes in standard macroeconomic variables. Furthermore, analysis of variance decompositions indicated that GNP variation between 13% and 16% is explained by changes in consumer sentiment. Less impressive, but still positive, predictive power is reported in other studies. Lee and Shields (2000), examining UK manufacturing output trends over the period 1975–1993, report that forecasts of fluctuations in real economic activity are improved by including expected output alongside actual output. Similarly, Carroll *et al.* (1994), forecasting household expenditure, find that lagged consumer sentiment does have a degree of explanatory power in predicting current changes in household spending.

The inability of economic forecasters to predict the 1991 US recession using standard macroeconomic variables led Batchelor and Dua (1998) to investigate the role of consumer confidence and to consider whether indicators of confidence would have improved previous economic forecasts. Their results show that incorporating information on consumer confidence would have improved the forecasts in anticipating the 1991 US downturn. However, they are less sanguine about the more general value of indicators of consumer confidence in predicting business cycle activity. In particular, consumer confidence indicators would not have accurately predicted other significant business cycle episodes.

A related strand of the literature are those studies that have considered whether consumer confidence indicators are useful in predicting consumer expenditure. Acemoglu and Scott (1994) reject the rational expectations permanent income hypothesis for the UK because of the strong predictive power of consumer confidence, rather than labour income or other macroeconomic variables, in anticipating fluctuations in consumption. Delorme, Kamerschen and Voeks (2001), building on the work of
Carroll et al. (1994), test the rational expectations hypothesis for the US, comparing their results with those of Acemoglu and Scott (1994). The findings presented by Delorme et al. (2001) are supportive of the rational expectations version of the permanent income model and also suggest that the predictive power of consumer confidence is lower for the US than it is for the UK.

Eppright et al. (1998) use VAR analysis on US data to investigate whether indices of aggregate consumer sentiment and expectations possess any information not contained in other economic indicators. Their analysis reveals that measures of consumer expectations provide predictive power over and above other leading indicators. Finally, Bodo, Golinelli and Parigi (2000) find that business confidence indices have forecasting capability over and above other leading indicators in the Euro area using autoregressive integrated moving-average (ARIMA) and cointegrated VAR techniques.

III. Data

A novel feature of the present study is that it uses direct measures of consumer and business expectations that are available for European Union member states, enabling an intercountry comparative analysis. The analysis presented here focuses on four countries, UK, France, Italy and the Netherlands, using quarterly data for the period 1983–98. The measures of consumer and business confidence used are drawn from European Economy Consumer Survey Results and Business and Consumer Survey Results, respectively (European Commission, 1997, 2004).

Both indicators are simple averages of responses to a range of questions (shown in the Appendix) and are constructed so that each indicator lies within the range −100 to +100, where positive values indicate optimism. For the business survey there are three responses reported: the percentage of positive replies (i.e. up or above normal), \( P \); the percentage of replies corresponding to the intermediate option (i.e. unchanged or normal), \( E \); and the percentage of negative replies (i.e. down or below normal), \( M \). Clearly, \( P + E + M = 100\% \), and the percentage of net positive or optimistic responses (\( B \)), is given by \( B = P - M \). For the consumer survey there are six responses: \( PP \) and \( P \) refer to ‘get a lot better’ and ‘get a little better’, respectively.

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2 Although the confidence data are available at a monthly frequency, GDP is only quarterly. While others have used monthly industrial production, which is specific to manufacturing to proxy economic activity (e.g. Andreou, Osborn and Sensier, 2000), it is debatable whether or not this is a good indicator. For example, in 1995 industrial production accounted for only 26.6% of UK GDP. Moreover, Andreou et al. (2000) note that industrial production is twice as volatile as quarterly GDP in the UK. Consequently, conclusions may differ from studies based on industrial production data in comparison with those using GDP because GDP covers all industrial sectors while industrial production data only encapsulates manufacturing. The measures of business and consumer confidence indicators also relate to all sectors not just manufacturing.

3 http://europa.eu.int/comm/economy_finance/indicators/businessandconsumersurveys_en.htm.

4 While the consumer questionnaire is at the household level, very little work has examined responses to expectations questions at a micro (household or individual) level. Exceptions are Brown et al. (2005) and Brown and Taylor (2006), who consider how expectations about future income, i.e. confidence, affect household financial decisions.
Similarly, $MM$ and $M$ refer to ‘get a lot worse’ and ‘get a little worse’, respectively. In this case, $B$ calculated as $B = (PP + \frac{1}{2}P) - (\frac{1}{2}M + MM)$, which again represents net optimism. Both the business and consumer surveys enable a summary, given as a single figure calculated from the arithmetic average of the responses, to be derived for each of the questions.\textsuperscript{5,6} The consumer and business confidence data are shown with the growth in GDP for each country in Figure 1. The growth in GDP is scaled to fit the vertical axis together with the change in confidence measures over time. Without pre-empting the analysis presented here, the data presented in the charts suggest that fluctuations in the measures of business and consumer confidence in all four countries tend to lead movements in output.\textsuperscript{7}

In addition to confidence indicators, other potential leading indicators, as identified in previous studies, employed in the analysis are the real wage, employment, consumer expenditure, government expenditure, gross fixed investment, money supply (both broad and narrow measures), unemployment rate, interest rate and the real effective exchange rate. These data are available for each country from Datastream.

IV. Cross-sectional properties

In this section, the cross-sectional properties of the confidence data are examined for each country. A number of papers have considered cross-correlations among variables to determine whether such variables are countercyclical or procyclical (e.g. Blackburn and Ravn, 1992; Millard, Scott and Sensier, 1997; Andreou \textit{et al.}, 2000). A common technique is to de-trend the data via the Hodrick–Prescott (HP) filter before examining comovement between variables (Hodrick and Prescott, 1997). However, there are a number of problems with the HP method, especially when data are non-stationary, which may generate spurious results (Stock and Watson, 1999). In addition, Canova (1998) has shown that de-trending may affect the cyclical component of the variables concerned and thus the estimated unconditional correlation coefficients, and Harvey and Jaeger (1993) report that artificial correlations between series may be introduced by de-trending data.

\textit{den Haan} (2000) provides an alternative framework for examining correlations between series based on correlations from VAR forecast errors at different horizons.

\textsuperscript{5}We add 100 to this index to enable us to convert the data to logarithms.

\textsuperscript{6}It should be noted that there are alternative methods for quantifying survey responses. For example, Cunningham, Smith and Weale (1998), Mitchell, Smith and Weale (2002) and Driver and Urga (2004) show how qualitative survey responses, such as those used herein, can be converted into quantitative data. Typically, however, these methods rely on having information upon the underlying microlevel data, i.e. firm and household responses from which the aggregate business and consumer confidence indicators are derived. Unfortunately, we cannot adopt such an approach as we do not have access to this microdata, which is necessary in order to decompose the balance summary statistic into its constituent parts, e.g. for the consumer confidence questions the percentage of respondents in each of the six categories is required to be able to adopt the aforementioned methodologies (Driver and Urga, 2004).

\textsuperscript{7}It should be noted that because the measures of confidence are estimated as a balance of responses, the differences observed across countries could reflect differences in the distribution of outcomes rather than the intensity of fluctuations in sentiment.
Figure 1. Plots of consumer, business confidence and growth in GDP across countries

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This approach can accommodate both stationary and integrated variables and thus does not require prefiltering. Furthermore, the method does not require those identification restrictions needed for VAR decompositions. Consider the following VAR:
\[ Z_t = \mu + \alpha_0 t + \alpha_1 t^2 + \sum_{i=1}^{p} A_i Z_{t-i} + v_t \]  

(1)

where \( Z_t \) is an \( n \)-vector of random variables, potentially both stationary and non-stationary variables, including output \( y_t \) and a potential leading indicator \( C_t \), such as a measure of consumer confidence; \( \mu \) an \( n \)-vector of constant terms or possibly a matrix of deterministic coefficients; \( t \) a time trend; \( A_i \) are \( n \times n \) matrices of coefficients; \( v_t \) an \( n \)-vector of error terms; and \( p \) the total number of lags. Denote \( k \)-period-ahead forecasts of output \( y_t \) and its \( k \)-period-ahead forecast error as \( E_{yt+k} \) and \( y_{fe}^{t+k} \), respectively. Similarly, one can define \( E_{Ct+k} \) and \( C_{fe}^{t+k} \). The correlation coefficient between \( y_{fe}^{t+k} \) and \( C_{fe}^{t+k} \) is denoted by \( \text{cor}(k) \) and it is this measure which is the primary statistic of interest. (For further details, see den Haan, 2000.)

The aforementioned methodology is applied to the data to examine the correlations between the confidence indicators and the business cycle. Bivariate VARs are estimated in levels, that is \( Z_t = (y_t, C_t) \prime \), and 95% confidence bands are constructed using bootstrap methods. Optimal lag length is selected using Akaike information criterion (AIC). Three versions of equation (1) are estimated, namely, without a time trend, with a time trend and imposing a unit root.

The results of the correlations between output and consumer and business confidences are shown for the UK, France, Italy and the Netherlands in Figure 2. The focus here is on the case of no trend, although the results are also qualitatively and quantitatively consistent when either a time trend or a unit root is imposed, implying robustness in our findings. Across countries the correlation between output and confidence is significant at the 5% level and the correlation is predominantly positive for a forecast horizon of eight quarters ahead, implying that confidence indicators are procyclical leading indicators. Other potential leading indicators are also found to have a statistically significant relationship with output.

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8 den Haan (2000) has shown that, if some of the time series in the VAR are integrated, the correlation coefficients may not converge, but consistent estimation is still feasible for a fixed \( k \). Conversely, if the data are stationary, then the correlation coefficient of the forecast errors will converge to the unconditional correlation coefficient of the two series as \( k \) approaches infinity.

9 This is consistent with the work of den Haan (2000) and Vázquez (2002), where the latter employs den Haan’s methodology to consider the comovement between output and prices in EU15 countries.

10 Note in an earlier version of this paper we also considered co-movement between confidence indicators and output via data de-trended using the HP filter. The results were consistent with those presented here.

11 The results also indicate that the real wage is countercyclical in Italy and the Netherlands. This is somewhat of a surprise because the majority of evidence suggests that real wages exhibit modest cyclical, though correlations with output are often insignificant (Keane, Moffitt and Runkle, 1988; Abel, Bernanke and McNabb, 1998). Other variables that are found to be countercyclical are unemployment and the exchange rate (with the exception of the UK). Consumer expenditure and investment are found to be procyclical across countries, which is consistent with other international evidence (Bergman, Bordo and Jonung, 1998).
Business cycles and the role of confidence

Figure 2. Relationship between confidence indicators and output across countries

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V. Forecasts

We have established that business and/or consumer confidence are significant procyclical leading indicators for the four European economies under consideration. Their predictive power is now examined using two approaches: first, we investigate the power of confidence indicators in predicting the likelihood of an economic downturn as a discrete event. We then undertake a more standard quantitative forecasting approach based on VAR estimates.

Forecast probits: can confidence indicators predict economic downturns?

The first stage of the forecasting analysis focuses on predicting economic downturns rather than on quantitative measures of economic activity. The ability to predict an economic downturn is clearly of importance to policy makers. For example, Sensier et al. (2004) note that policy makers and economic agents are likely to be more concerned about absolute declines and expansions in activity rather than quantitative point measures of economic growth. Moreover, focusing attention on a discrete dependent variable is consistent with the view that economies evolve within distinct discrete states (Hamilton, 1989). Indeed, there has been a great deal of interest in models that predict such regimes, although the majority of the empirical work has been for the US (see, e.g. Birchenhall et al., 1999; Chauvet and Potter, 2002). The particular approach employed in the present study follows Estrella and Mishkin (1998) and involves estimating a forecast probit model of the likelihood of an economic downturn defined by the following relationship:

\[ s_{t+k}^* = x_t \beta + \epsilon_t \]  

(2)

where \( s_{t+k}^* \) is an unobservable variable, which determines the occurrence of an economic downturn at time \( t \) and \( k \) is the length of the forecast horizon. The error term, \( \epsilon_t \), is normally distributed, and \( x_t \) is a matrix of independent variables including a constant term with a corresponding vector of coefficients \( \beta \). The observable economic downturn indicator \( r_t \) is related to the above model as follows:

\[ r_t = \begin{cases} 1, & \text{if } s_t^* > 0 \\ 0, & \text{otherwise} \end{cases} \]  

(3)

The form of the estimating equation is:

\[ \text{Prob}(r_{t+k} = 1) = F(x_t \beta) \]  

(4)

where \( F \) is the cumulative normal distribution function corresponding to \( \epsilon_t \) and the model is estimated by maximum likelihood. The principal measure of the model’s

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12 Sensier et al. (2004) adopt a similar approach to predicting classical business cycle regimes in Europe explicitly considering the role of domestic and international influences, though they focus upon the probability of a business cycle expansion. Hardy and Pazarbaşıoğlu (1999) also employ discrete dependent variable analysis to investigate which macroeconomic and financial variables can be useful leading indicators of banking crises across a large number of countries.
explanatory power is a pseudo-$R^2$, commonly used in probit forecast models (Estrella, 1998). We also report the log-likelihood statistic and its $P$-value as well as the percentage of $r_t$ correctly predicted.

Standard $t$-ratios cannot be used for the purposes of hypothesis testing after predicting two or more quarters ahead, because an overlapping data problem exists in that the forecast horizon is longer than the observation interval. Forecast errors are likely to be serially correlated, and so $t$-statistics are calculated using standard errors adjusted for the overlapping data problem as suggested by Newey and West (1987).

Various methods have been used to define a business cycle downturn. Typically, these incorporate one or more periods of below-average GDP. In addition, the European Cycle Research Institute (ECRI) dates classical turning points for various countries and has been previously used by Sensier et al. (2004). The methodology employed by the ECRI is identical to that used by the National Bureau of Economic Research for the US. In our empirical analysis, we therefore define an economic downturn for each country, i.e. $r_t = 1$, in three alternative ways:

(i) $r_t = 1$ if the growth in GDP for country $c$ is below the sample average (1983–98) for up to two consecutive quarters in country $c$;

(ii) $r_t = 1$ if the growth in GDP for country $c$ is below the sample average (1983–98) for more than two consecutive quarters in country $c$; and

(iii) $r_t = 1$ if the growth in GDP is identified as an ECRI trough.

For example, in the UK the average growth rate in GDP over the period 1983–98 was 3.2%. Based on item (i) in the preceding list, $r_t = 1$ if the growth in GDP is below 3.2% for one or two consecutive quarters; otherwise $r_t = 0$. Based on the definition in item (ii) in the preceding list, $r_t = 1$ if the growth in GDP is less than 3.2% for more than two consecutive quarters; otherwise $r_t = 0$. The forecast horizon we focus on is four quarters ahead, so $k = 4$. We also compare our results from defining the data in log levels, growth rates and as HP-filtered data. Although HP-filtered data are widely used in the literature, it is subject to the reservations noted earlier. Our preference is, therefore, to focus on data in log levels (for ease of interpretation) or growth rates (as this may alleviate problems associated with non-stationarity). For each country we have nine sets of results (six in the case of the Netherlands), defined by different definitions of business cycle phases and alternative definitions of the data in the $x_t$ matrix.

The results of this analysis are shown in Tables 1 to 4. In each table we include all potential leading indicators in $x_t$ to consider whether confidence has a role to play.

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13 The ECRI provides classical business cycle turning points for France, Italy and the UK (and other countries); details can be found at: http://www.businesscycle.com/chronologies. Unfortunately, no business cycle dating currently exists for the Netherlands.

14 We obtained results of the probability for an economic downturn for $k = 1, 2, 3$ and 4, but for brevity only report the results for the longest forecast horizon. Our findings were largely consistent over different forecast horizons.
### TABLE 1

**Results for probit model k = 4 quarters ahead – UK**

|                          | Log levels          | Growth                   | HP-filtered               |
|--------------------------|---------------------|--------------------------|---------------------------|
|                          | M.E.    | t-statistic | M.E.    | t-statistic | M.E.    | t-statistic |
| **(a) r = 1 if growth in GDP below average for up to two quarters** |          |             |          |             |          |             |
| Consumer confidence      | −8.59   | 1.28        | −6.42   | 1.75*     | 10.63   | 1.39        |
| Business confidence      | −24.49  | 3.37*       | −14.77  | 2.61*     | −23.32  | 2.52*       |
| Log-likelihood           | 38.15   | *P = 0.000* | 29.96   | *P = 0.002* | 28.88   | *P = 0.003* |
| Pseudo-$R^2$             | 0.430   |             | 0.389   |             | 0.326   |             |
| Percentage of (0/1) correctly forecast | 79.7%   |             | 67.2%   |             | 75.1%   |             |
| **(b) r = 1 if growth in GDP below average for more than two quarters** |          |             |          |             |          |             |
| Consumer confidence      | −7.05   | 1.88*       | −6.06   | 2.87*     | 8.47    | 1.68        |
| Business confidence      | −20.51  | 2.55*       | −28.83  | 1.85*     | −25.06  | 2.46*       |
| Log-likelihood           | 41.63   | *P = 0.000* | 51.24   | *P = 0.000* | 31.22   | *P = 0.002* |
| Pseudo-$R^2$             | 0.497   |             | 0.410   |             | 0.426   |             |
| Percentage of (0/1) correctly forecast | 87.5%   |             | 71.9%   |             | 82.8%   |             |
| **(c) r = 1 if growth in GDP coincides with ECRI turning point** |          |             |          |             |          |             |
| Consumer confidence      | −2.63   | 2.57*       | −1.94   | 2.41*     | −0.01   | 0.33        |
| Business confidence      | −4.32   | 2.85*       | −1.16   | 3.01*     | −0.08   | 3.52*       |
| Log-likelihood           | 32.47   | *P = 0.001* | 37.03   | *P = 0.000* | 40.92   | *P = 0.000* |
| Pseudo-$R^2$             | 0.526   |             | 0.604   |             | 0.663   |             |
| Percentage of (0/1) correctly forecast | 82.3%   |             | 82.2%   |             | 80.6%   |             |

*Notes:* M.E. refers to the marginal effect evaluated at the sample mean. All results are based upon controlling for all potential leading indicators, which are jointly significant at the 5% level. *Denotes statistical significance at the 5% level.
### TABLE 2

Results for probit model \( k = 4 \) quarters ahead – France

|                | Log levels M.E. | Growth M.E. | HP-filtered M.E. |
|----------------|-----------------|-------------|------------------|
|                | \( t \)-statistic | \( t \)-statistic | \( t \)-statistic |
| \( a \) \( r = 1 \) if growth in GDP below average for up to two quarters | | |
| Consumer confidence | -5.15 | 1.39 | -10.37 | 0.71 | 13.04 | 1.31 |
| Business confidence | -19.77 | 2.64* | -6.34 | 1.96* | -16.04 | 2.64* |
| Log-likelihood | 22.81 \( P = 0.003 \) | 21.38 \( P = 0.004 \) | 18.29 \( P = 0.010 \) |
| Pseudo-\( R^2 \) | 0.364 | 0.304 | 0.212 |
| Percentage of (0/1) correctly forecast | 73.4% | 53.1% | 76.6% |
| \( b \) \( r = 1 \) if growth in GDP below average for more than two quarters | | |
| Consumer confidence | -3.04 | 1.35 | -0.78 | 0.23 | 6.42 | 0.84 |
| Business confidence | -7.60 | 1.94* | -10.54 | 2.04* | -8.84 | 1.90* |
| Log-likelihood | 32.16 \( P = 0.000 \) | 21.11 \( P = 0.004 \) | 21.06 \( P = 0.005 \) |
| Pseudo-\( R^2 \) | 0.380 | 0.321 | 0.316 |
| Percentage of (0/1) correctly forecast | 87.5% | 79.7% | 81.3% |
| \( c \) \( r = 1 \) if growth in GDP coincides with ECRI turning point | | |
| Consumer confidence | -0.53 | 1.40 | -0.84 | 0.43 | 0.98 | 0.35 |
| Business confidence | 0.66 | 0.80 | -8.88 | 3.50* | 1.20 | 0.51 |
| Log-likelihood | 15.46 \( P = 0.015 \) | 19.83 \( P = 0.009 \) | 11.61 \( P = 0.156 \) |
| Pseudo-\( R^2 \) | 0.169 | 0.267 | 0.178 |
| Percentage of (0/1) correctly forecast | 85.9% | 84.4% | 87.5% |

Notes: M.E. refers to the marginal effect evaluated at the sample mean. All results are based upon controlling for all potential leading indicators, which are jointly significant at the 5% level. *Denotes statistical significance at the 5% level.
TABLE 3

Results for probit model \( k = 4 \) quarters ahead – Italy

|                  | Log levels | Growth | HP-filtered |
|------------------|------------|--------|-------------|
|                  | M.E.       | t-statistic | M.E. | t-statistic | M.E. | t-statistic |
| (a) \( r = 1 \) if growth in GDP below average for up to two quarters |            |         |             |            |         |             |
| Consumer confidence | -1.43      | 2.94*   | -3.79   | 1.89*       | -6.60 | 3.58*       |
| Business confidence | 1.42       | 0.34    | -5.76   | 0.93        | -2.53 | 0.64        |
| Log-likelihood    | 20.36 \( P = 0.004 \) |         | 20.81 \( P = 0.003 \) |         | 19.63 \( P = 0.005 \) |         |
| Pseudo-\( R^2 \)  | 0.231      |         | 0.239   |             | 0.223 |             |
| Percentage of (0/1) correctly forecast | 65.6%      |         | 70.3%   |             | 76.6% |             |
| (b) \( r = 1 \) if growth in GDP below average for more than two quarters |            |         |             |            |         |             |
| Consumer confidence | -0.09      | 1.85*   | 0.76    | 0.39        | -0.05 | 2.27*       |
| Business confidence | 0.14       | 0.45    | -8.58   | 2.12*       | 0.01  | 0.63        |
| Log-likelihood    | 30.77 \( P = 0.000 \) |         | 9.66 \( P = 0.140 \) |         | 39.41 \( P = 0.000 \) |         |
| Pseudo-\( R^2 \)  | 0.600      |         | 0.638   |             | 0.258 |             |
| Percentage of (0/1) correctly forecast | 80.6%      |         | 82.8%   |             | 82.2% |             |
| (c) \( r = 1 \) if growth in GDP coincides with ECRI turning point |            |         |             |            |         |             |
| Consumer confidence | 0.09       | 0.66    | -0.79   | 1.74*       | -4.87 | 1.83*       |
| Business confidence | -0.32      | 0.50    | -4.77   | 2.14*       | -3.26 | 2.35*       |
| Log-likelihood    | 18.72 \( P = 0.005 \) |         | 21.77 \( P = 0.002 \) |         | 42.27 \( P = 0.000 \) |         |
| Pseudo-\( R^2 \)  | 0.360      |         | 0.387   |             | 0.813 |             |
| Percentage of (0/1) correctly forecast | 89.1%      |         | 84.4%   |             | 85.3% |             |

Notes: M.E. refers to the marginal effect evaluated at the sample mean. All results are based upon controlling for all potential leading indicators, which are jointly significant at the 5% level. *Denotes statistical significance at the 5% level.
### TABLE 4
Results for probit model $k = 4$ quarters ahead – The Netherlands

|                      | Log levels |                         | Growth |                         | HP-filtered |
|----------------------|------------|--------------------------|--------|--------------------------|-------------|
|                      | M.E.       | t-statistic              | M.E.   | t-statistic              | M.E.        | t-statistic |
| (a) $r = 1$ if growth in GDP below average for up to two quarters |            |                          |        |                          |             |             |
| Consumer confidence  | -2.05      | 2.22*                    | -10.51 | 2.06*                    | -3.08       | 2.02*       |
| Business confidence  | 6.21       | 0.64                     | 2.69   | 0.15                     | 4.74        | 1.36        |
| Log-likelihood       | 23.23 $P=0.003$ |                | 21.38 $P=0.004$ |                | 19.23 $P=0.007$ |
| Pseudo-$R^2$         | 0.35       |                          | 0.323  |                          | 0.299       |             |
| Percentage of (0/1) correctly forecast | 56.3% |                          | 65.6%  |                          | 62.5%       |             |
| (b) $r = 1$ if growth in GDP below average for more than two quarters |            |                          |        |                          |             |             |
| Consumer confidence  | -3.85      | 1.99*                    | -10.59 | 2.99*                    | 0.72        | 0.32        |
| Business confidence  | 0.35       | 0.15                     | 0.57   | 0.05                     | -0.54       | 0.07        |
| Log-likelihood       | 24.81 $P=0.001$ |                | 15.77 $P=0.011$ |                | 11.88 $P=0.014$ |
| Pseudo-$R^2$         | 0.402      |                          | 0.270  |                          | 0.202       |             |
| Percentage of (0/1) correctly forecast | 82.8% |                          | 79.7%  |                          | 84.4%       |             |

**Notes:** M.E. refers to the marginal effect evaluated at the sample mean. All results are based upon controlling for all potential leading indicators, which are jointly significant at the 5% level. *Denotes statistical significance at the 5% level.
in addition to the forecasting ability of other leading indicators. Each table is split into three panels based on the three definitions of an economic downturn noted in the preceding list. The first column of each table specifies all independent variables in log levels, as considered by Estrella and Mishkin (1998), the second column in growth rates, as considered by Sensier et al. (2004), and the final column uses HP-filtered data. All marginal effects are evaluated at the sample mean values of other variables.

The results for the UK clearly show that there is a significant role for confidence indicators in predicting below-period-average growth. Regardless of how the variables are defined, the results show that confidence has predictive power. The results are especially strong for business confidence. For example, where a downturn is defined in terms of below-period-average GDP growth, by either definition (i) or (ii) from the preceding list and defining the variables in log levels, a 1 percentage point increase in business confidence at time $t$ decreases the probability of a downturn in activity by between 20 and 25 percentage points at $t + 4$. The impact of confidence is smaller, though still significant, if the turning points are defined by ECRI dating. In this case, a 1 percentage point increase in business confidence at time $t$ decreases the probability of a downturn in activity by around 4 percentage points at $t + 4$. Defining all the independent variables in terms of growth rates or as HP-filtered data also clearly shows a role for confidence across different definitions of an economic downturn. Hence, the UK results are robust to alternative definitions of an economic downturn and how the data are defined, although this clearly changes the functional form and interpretation of the marginal effects.

Turning to the results for the other three countries, it is clear that confidence has predictive power in explaining discrete movements in economic activity for these as well. In terms of forecasting an economic downturn, business confidence plays a role in France, whereas consumer confidence is of greater importance (and/or statistical significance) in Italy and the Netherlands. For example, in the Netherlands a 1 percentage point increase in consumer confidence reduces the probability of a downturn in economic activity at $t + 4$ by between 2 and 4 percentage points depending on the horizon that the growth in GDP is below trend. It is also noticeable from Tables 1 to 4 that the impact of business and consumer confidence is larger in the UK than in the other three countries, the only exception being the impact of consumer confidence in the Netherlands. In terms of model fit across countries, the pseudo-$R^2$ is high, the log-likelihood is always significant, and there is a high degree of forecasting success.

**Dynamic forecasts of output**

Having found that confidence indicators play a role in being able to predict the likelihood of an economic downturn, we now consider whether such variables are useful in obtaining quantitative point estimates of GDP activity. A common method for constructing forecasts of $t + k$ periods ahead is by applying VAR estimation. Using
equation (1), estimates of $\hat{A}_i$ can be used to construct a $k$-step-ahead forecast as follows:

$$\hat{Z}_t(k) = \hat{\mu} + \sum_{i=1}^{p} \hat{A}_i \hat{Z}_t(k-i).$$

(5)

As such, $\hat{Z}_t(k)$ highlights the fact that forecasts are a function of the number of periods ahead, $k$. The forecast equation is also recursive in that the prediction at $k+1$ depends on the prediction at $k$. In the analysis presented here, equation (1) is estimated as a multivariate VAR over the period up to the fourth quarter of 1997 so as to gain an out-of-sample forecast using equation (5). Forecasts are thus obtained for four periods ahead, namely, 1998 first quarter to 1998 fourth quarter, thus matching the forecast horizon used in predicting downturns. Optimal lag length is selected using the AIC. We estimate equations (1) and (5) by, first, with the VAR incorporating the growth in GDP and all potential leading indicators $L$, but excluding confidence measures so that $Z_t = (y_t, L_t)'$, and then including consumer and business confidence $CC_t$ and $BC_t$ in the VAR so that $Z_t = (y_t, L_t, CC_t, BC_t)'$. We then compare the forecast errors from the two VARs using the root mean squared error (RMSE), which is defined as

$$\text{RMSE} = \sqrt{\frac{1}{k-1} \sum_{k} (Z_t(k) - \hat{Z}_t(k))^2}$$

and the mean absolute error (MAE), which is defined as the average of the absolute values of the forecast errors:

$$\text{MAE} = \frac{1}{k-1} \sum_{k} |(Z_t(k) - \hat{Z}_t(k))|.$$  

(7)

If confidence indicators are useful in forecasting GDP, then both the RMSE and MAE will be reduced by their inclusion in the underlying multivariate VAR.

The results for the four-period out-of-sample forecasts are shown in Table 5, with forecasts in bold and 95% confidence intervals also shown. Clearly, across countries the forecasts fall within the limits when both including and excluding confidence indicators in the VAR. The earlier analysis showed for each country an unambiguous role for confidence indicators in predicting the probability of an economic downturn. However, comparing the RMSE and MAE in each case considered, the quantitative point forecast results suggest that confidence indicators have added forecasting ability over and above other leading indicators only in the UK and the Netherlands, because only in these two countries do the values of RMSE and MAE fall when confidence indicators are included in the VAR. Specifically, RMSE and MAE decrease by 5.2% and 6.6%, respectively, for the UK, and RMSE and MAE fall by 5.3% and 3.6%, respectively, for the Netherlands.

So far the analysis has not considered whether the improvements in forecasting ability as a result of including confidence indicators in the VAR are statistically
## TABLE 5

Results from VAR forecasts $k$ quarters ahead

|                | $K = 1$          | $K = 2$          | $K = 3$          | $K = 4$          |
|----------------|------------------|------------------|------------------|------------------|
|                | Lower        | Forecast       | Upper       | Lower        | Forecast       | Upper       | Lower        | Forecast       | Upper       |
| **UK**         |                |                 |             |                |                 |             |                |                 |             |
| Confidence included in VAR | 0.0012 | **0.0175** | 0.0339 | 0.0053 | **0.0234** | 0.0415 | −0.0020 | **0.0177** | 0.0373 | −0.0030 | **0.0178** | 0.0387 |
| Confidence excluded in VAR | −0.0041 | **0.0119** | 0.0278 | −0.0068 | **0.0128** | 0.0323 | −0.0123 | **0.0093** | 0.0310 | −0.0122 | **0.0097** | 0.0316 |
| RMSE and MAE confidence included | 0.0073, 0.0071 |                 |             |                |                 |             |                |                 |             |
| RMSE and MAE confidence excluded | 0.0077, 0.0076 |                 |             |                |                 |             |                |                 |             |
| Diebold–Mariano $r_{DM}$ using RMSE | −2.646 | $P = 0.0082$ | −2.418 | $P = 0.0000$ |                 |             |                |                 |             |
| **France**     |                |                 |             |                |                 |             |                |                 |             |
| Confidence included in VAR | 0.0326 | **0.0416** | 0.0507 | −0.0244 | **0.0046** | 0.0153 | 0.0089 | **0.0472** | 0.0856 | −0.1715 | **0.1058** | −0.0402 |
| Confidence excluded in VAR | −0.0007 | **0.0175** | 0.0358 | −0.0169 | **0.0057** | 0.0284 | −0.0263 | **0.0010** | 0.0243 | −0.0294 | **0.0028** | 0.0349 |
| RMSE and MAE confidence included | 0.0129, 0.0152 |                 |             |                |                 |             |                |                 |             |
| RMSE and MAE confidence excluded | 0.0097, 0.0095 |                 |             |                |                 |             |                |                 |             |
| Diebold–Mariano $r_{DM}$ using RMSE | 1.233 | $P = 0.0902$ | 1.404 | $P = 0.0857$ |                 |             |                |                 |             |
| **Italy**      |                |                 |             |                |                 |             |                |                 |             |
| Confidence included in VAR | −0.0098 | **0.0059** | 0.0215 | −0.0127 | **0.0065** | 0.0258 | −0.0157 | **0.0043** | 0.0242 | −0.0125 | **0.0076** | 0.0276 |
| Confidence excluded in VAR | −0.0183 | **0.0011** | 0.0160 | −0.0125 | **0.0059** | 0.0242 | −0.0158 | **0.0033** | 0.0224 | −0.0149 | **0.0044** | 0.0237 |
| RMSE and MAE confidence included | 0.0072, 0.0071 |                 |             |                |                 |             |                |                 |             |
| RMSE and MAE confidence excluded | 0.0070, 0.0068 |                 |             |                |                 |             |                |                 |             |
| Diebold–Mariano $r_{DM}$ using RMSE | 0.382 | $P = 0.7023$ | 1.147 | $P = 0.2513$ |                 |             |                |                 |             |
| **The Netherlands** |                |                 |             |                |                 |             |                |                 |             |
| Confidence included in VAR | −0.0125 | **0.0121** | 0.0367 | −0.0248 | **0.0027** | 0.0303 | −0.0215 | **0.0083** | 0.0380 | −0.0226 | **0.0066** | 0.0358 |
| Confidence excluded in VAR | −0.0074 | **0.0184** | 0.0443 | −0.0224 | **0.0061** | 0.0346 | −0.0220 | **0.0093** | 0.0407 | −0.0124 | **0.0186** | 0.0496 |
| RMSE and MAE confidence included | 0.0108, 0.0107 |                 |             |                |                 |             |                |                 |             |
| RMSE and MAE confidence excluded | 0.0114, 0.0111 |                 |             |                |                 |             |                |                 |             |
| Diebold–Mariano $r_{DM}$ using RMSE | 4.427 | $P = 0.0015$ | 5.655 | $P = 0.0000$ |                 |             |                |                 |             |

Note: ‘Lower’ and ‘Upper’ denote 95% confidence intervals for the forecast.
significant. In order to address their quantitative importance, we implement a test proposed by Diebold and Mariano (1995). The test is calculated as follows:

\[
 r_{DM} = \exp \left\{ \frac{E \left[ g(y_{f1+k}^e) - g(y_{f2+k}^e) \right]}{\sqrt{2\pi f_d(0)}} \right\}.
\]  (8)

Forecast errors of output \( k \) periods ahead from the two competing models (one model includes confidence indicators and the other model excludes confidence indicators) are given by \( y_{fj+k}^e \), \( j = 1, 2 \), and \( g(y_{fj+k}^e) \) is the loss function. \( f_d(0) \) is the spectral density of the numerator at frequency zero. Because we use RMSE from equation (6) and MAE from equation (7), we thus calculate two versions of equation (8). In Table 5 we report this statistic and show the associated probability from testing the null hypothesis of equality between the two comparison forecasts. Only in the UK and the Netherlands is the null hypothesis rejected, which favours the inclusion of confidence indicators in the VAR for these two countries.

The final analysis we have undertaken considers impulse responses that show the response of GDP to unit shocks in the VAR. Figure 3 presents the impulse response functions over time along with 95% confidence intervals. Generally, a one-unit increase in either consumer or business confidence results in a one-off increase in GDP activity that dissipates by around the fifth period. Exceptions are France and the impact of consumer confidence in the UK. For France, while GDP activity responds in the expected way to a change in business confidence, an increase in consumer confidence actually reduces activity, although again this dies out by around the fifth period. The only impact on GDP activity that has an effect beyond the fifth period is consumer confidence in the UK. Consumer confidence has a positive impact up until the fifth period and then decreases, dissipating by the end of the horizon.

VI. Conclusions

This paper has considered the performance of consumer and business confidence indicators in predicting economic activity across four European countries. Having found significant correlations between confidence indicators and economic cycles, the analysis focused upon, first, the performance of confidence indicators in predicting the likelihood of economic downturns using forecast probits and, second, dynamic forecasting using VAR techniques.

The results obtained are encouraging, showing that both consumer and business confidence indicators have good predictive power in identifying turning points in the business cycle. This is evident based on different definitions of a cycle turning point and altering the functional form of the model, which suggests that the results are relatively robust.

15Given GDP growth and two competing forecasts, implementing the test involves applying a loss criterion (using either MAE or RMSE) and then calculating a number of measures of predictive accuracy that allow the null hypothesis of equal accuracy to be tested. Specifically, we test that the mean difference between the loss criteria for the two forecasts is zero; see Diebold and Mariano (1995) for further details.
Figure 3. Impulse responses of GDP growth to business confidence and consumer confidence across countries

In terms of forecasting quantitative point estimates of GDP, confidence indicators do a relatively good job in the UK and the Netherlands, significantly reducing the forecasting error associated with the prediction. However, although confidence indicators are useful in determining economic downturns in France and Italy, there is no gain in forecasting quantitative point estimates of GDP growth.

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Taken as a whole, our findings suggest that confidence indicators might usefully supplement macroeconomic models and forecasts of economic activity, hence potentially aiding policy makers.
References

Abel, A., Bernanke, B. and McNabb, R. (1998). *Macroeconomics: European Edition*, Addison-Wesley, New York.

Acemoglu, D. and Scott, A. (1994). ‘Consumer confidence and rational expectations: are agents beliefs consistent with economic theory?’, *Economic Journal*, Vol. 104, pp. 1–19.

Andreou, E., Osborn, D. and Sensier, M. (2000). ‘A comparison of the statistical properties of financial variables in the USA, UK and Germany over the business cycle’, *The Manchester School*, Vol. 68, pp. 396–418.

Ball, L. and Romer, D. (1991). ‘Sticky prices as coordination failure’, *American Economic Review*, Vol. 81, pp. 539–552.

Batchelor, R. and Dua, P. (1998). ‘Improving macro-economic forecasts: the role of consumer confidence’, *International Journal of Forecasting*, Vol. 14, pp. 71–81.

Bergman, M., Bordo, M. and Jonung, L. (1998). ‘Historical evidence on business cycles: the international evidence’, in Fuhrer J. G. and Schuh S. (eds), *Beyond Shocks: What Causes Business Cycles?* Federal Reserve Bank of Boston, Conference Series No. 2, Boston, pp. 65–113.

Birdenhall, C., Jessen, H., Osborn, D. and Simpson, P. (1999). ‘Predicting US business-cycle regimes’, *Journal of Business and Economic Statistics*, Vol. 17, pp. 313–323.

Birchenhall, C., Jessen, H., Osborn, D. and Simpson, P. (1999). ‘Predicting US business-cycle regimes’, *Journal of Business and Economic Statistics*, Vol. 17, pp. 313–323.

Blackburn, K. and Ravn, M. (1992). ‘Business cycles in the United Kingdom: facts and fictions’, *Economica*, Vol. 59, pp. 383–401.

Bodo, G., Golinelli, R. and Parigi, G. (2000). ‘Forecasting industrial production in the Euro area’, *Empirical Economics*, Vol. 25, pp. 541–561.

Bram, J. and Ludvigson, S. (1998). ‘Does consumer confidence forecast household expenditure? A sentiment index horse race’, *Federal Reserve Bank of New York Policy Review*, Vol. 4, pp. 59–78.

Brown, S. and Taylor, K. (2006). ‘Financial expectations, consumption and saving: a microeconomic analysis’, *Fiscal Studies*, Vol. 27, pp. 313–338.

Brown, S., Garino, G., Taylor, K. and Wheatley Price, S. (2005). ‘Debt and financial expectations: an individual and household analysis’, *Economic Inquiry*, Vol. 43, pp. 100–120.

Canova, F. (1998). ‘Detrending and business cycle facts’, *Journal of Monetary Economics*, Vol. 41, pp. 475–512.

Carroll, C., Fuhrer, J. and Wilcox, D. (1994). ‘Does consumer sentiment forecast household spending? If so, why?’, *American Economic Review*, Vol. 84, pp. 1397–1408.

Chauvet, M. and Potter, S. (2002). ‘Forecasting recessions using the yield curve in the presence of structural breaks’, *Economics Letters*, Vol. 77, pp. 245–253.

Cunningham, A., Smith, R. and Weale, M. (1998). ‘Measurement errors and data estimation: the quantification of survey data’, in Begg I. and Henry S. (eds), *Applied Economics and Public Policy*, Cambridge University Press, Cambridge.

Delorme, C., Kamerschen, D. and Voeks, L. (2001). ‘Consumer confidence and rational expectations in the United States compared with the United Kingdom’, *Applied Economics*, Vol. 33, pp. 863–869.

Diebold, F. X. and Mariano, R. S. (1995). ‘Comparing predictive accuracy’, *Journal of Business and Economic Statistics*, Vol. 13, pp. 253–263.

Driver, C. and Urga, G. (2004). ‘Transforming qualitative survey data: performance comparisons for the UK’, *Oxford Bulletin of Economics and Statistics*, Vol. 66, pp. 71–89.

Eppright, D., Arguea, N. and Huth, W. (1998). ‘Aggregate consumer expectation indexes as indicators of future consumer expectations’, *Journal of Economic Psychology*, Vol. 19, pp. 215–235.

Estrella, A. (1998). ‘A new measure of fit for equations with dichotomous dependent variables’, *Journal of Business and Economic Statistics*, Vol. 16, pp. 198–205.

Estrella, A. and Mishkin, F. (1998). ‘Predicting US recessions: financial variables as leading indicators’, *Review of Economics and Statistics*, Vol. 80, pp. 45–61.
European Commission (1997). *The Joint Harmonised EU Programme of Business and Consumer Surveys. User Guide 6*. D.G. Economic and Financial Affairs, Luxembourg.

European Commission (2004). *The Joint Harmonised EU Programme of Business and Consumer Surveys. User Guide (updated 26/05/2004)*. D.G. Economic and Financial Affairs, Luxembourg.

Farmer, R. (1999). *Macroeconomics of Self-fulfilling Prophecies*, 2nd edn, MIT Press, Cambridge, MA.

den Haan, W. (2000). ‘The co-movement between output and prices’, *Journal of Monetary Economics*, Vol. 46, pp. 3–30.

Hamilton, J. (1989). ‘A new approach to the economic analysis of non-stationary time series and the business cycle’, *Econometrica*, Vol. 57, pp. 357–384.

Hardy, D. and Pazarbaşioğlu, C. (1999). ‘Determinants and leading indicators of banking crises: further evidence’, *IMF Staff Papers*, Vol. 46, pp. 247–258.

Harvey, A. C. and Jaeger, A. (1993). ‘Detrending, stylized facts and the business cycle’, *Journal of Econometrics*, Vol. 8, 231–247.

Hodrick, R. and Prescott, E. (1997). ‘Post-war US business cycles: an empirical investigation’, *Journal of Money, Credit and Banking*, Vol. 29, pp. 1–16.

Keane, M., Moffitt, R. and Runkle, D. (1988). ‘Real wages over the business cycle: estimating the impact of heterogeneity with micro data’, *Journal of Political Economy*, Vol. 96, pp. 1232–1266.

Lee, K. and Shields, K. (2000). ‘Expectations formation and business cycle fluctuations: an empirical analysis of actual and expected output in UK manufacturing, 1975-1996’, *Oxford Bulletin of Economics and Statistics*, Vol. 62, pp. 463–490.

Matsusaka, J. and Sbordone, A. (1995). ‘Consumer confidence and economic fluctuations’, *Economic Inquiry*, Vol. 33, pp. 296–318.

Milgrom, P. and Roberts, J. (1990). ‘Rationalizability, learning and equilibrium in games with strategic complementarities’, *Econometrica*, Vol. 58, pp. 1255–1277.

Millard, S., Scott, A. and Sensier, M. (1997). ‘The labour market over the business cycle: can theory fit the facts?’, *Oxford Review of Economic Policy*, Vol. 13, pp. 70–92.

Mitchell, J., Smith, R. and Weale, M. (2002). ‘Quantification of qualitative firm-level survey data’, *Economic Journal*, Vol. 112, pp. 117–135.

Newey, W. and West, K. (1987). ‘A simple positive semi-definite heteroskedasticity and autocorrelation consistent covariance matrix’, *Econometrica*, Vol. 55, pp. 703–708.

Ng, Y. (1992). ‘Business confidence and depression prevention: a mesoecoconomic perspective’, *American Economic Review*, Vol. 82, pp. 365–371.

Potter, S. (1999). ‘Fluctuations in confidence and asymmetric business cycles’, *Domestic Research Function, Federal Reserve Bank of New York. Staff report No. 66.*

Sensier, M., Artis, M., Osborn, D. and Birchenhall, C. (2004). ‘Domestic and international influences on business cycle regimes in Europe’, *International Journal of Forecasting*, Vol. 20, pp. 343–357.

Stock, J. H. and Watson, M. W. (1999). ‘Business cycle fluctuations in U.S. macroeconomic time series’, in Taylor J. B. and Woodford M. (eds), *Handbook of Macroeconomics*, Elsevier, Amsterdam.

Vázquez, J. (2002). ‘The co-movement between output and prices in the EU15 countries: an empirical investigation’, *Applied Economics Letters*, Vol. 9, pp. 957–966.

**Appendix**

**Harmonized consumer survey**

The consumer confidence indicator is the arithmetic average of results to the following five questions:

**Q1.** How does the financial situation of your household now compare with what it was 12 months ago?
(i) a lot better; (ii) a little better; (iii) stayed the same; (iv) a little worse; 
(v) a lot worse; (vi) don’t know.

Q2. How do you think the financial position of your household will change over the next 12 months?
(i) a lot better; (ii) a little better; (iii) stayed the same; (iv) a little worse; 
(v) a lot worse; (vi) don’t know.

Q3. How do you think the general economic situation in this country has changed over the last 12 months?
(i) a lot better; (ii) a little better; (iii) stayed the same; (iv) a little worse; 
(v) a lot worse; (vi) don’t know.

Q4. How do you think the general economic situation in this country will develop over the next 12 months?
(i) a lot better; (ii) a little better; (iii) stayed the same; (iv) a little worse; 
(v) a lot worse; (vi) don’t know.

Q5. Over the next 12 months, how do you think the amount of money you will spend on major purchases will compare with what you spent over the last 12 months?
(i) much more; (ii) a little more; (iii) about the same; (iv) a little less; (v) much less; (vi) don’t know.

Harmonized business survey

The business confidence indicator is the arithmetic average of results to the following:

Q1. Assessment of order book-levels
(i) above normal; (ii) normal; (iii) below normal.

Q2. Assessment of export order-book levels
(i) above normal; (ii) normal; (iii) below normal.

Q3. Production expectations for the months ahead
(i) up; (ii) unchanged; (iii) down.