Information, Business Survey Forecasts and Measurement of Output Trends in Six European Economies[*]

by

Kevin Lee and Kalvinder Shields
(Department of Economics, University of Leicester)

Abstract

Direct measures of expectations, derived from survey data, are used in a Vector Autoregressive (VAR) model of actual and expected manufacturing output series in six European economies over the period 1968-1998. No evidence is found with which to reject rationality in the derived expectations series when measurement error is appropriately taken into account. The VAR analysis is used to derive measures of trend output and these measures are compared with the trend obtained using only actual data. The relative merits of the derived series are described with reference to the efficiency and parsimony of their use of information.

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1 Introduction

The decomposition of output movements into a trend growth component and a cyclical component has been a central issue in macroeconomics. Considerable advances have been made in macroeconomics at the theoretical level as economists have attempted to identify the determinants of trend growth, the causes of cyclical deviations around the trend, and the extent to which the two should be considered independently of each other.[1] Similarly, at the empirical level, measures of 'trend', 'normal' or 'potential' output, and of 'underlying economic activity', and of 'output gaps' are regularly produced by academics and policy-makers. These measures are obtained using a wide variety of econometric methods and are at the heart of decision making in many different contexts, including the timing and conduct of macroeconomic policy.

In this paper, we provide three alternative measures of trend output in the manufacturing sectors of six European countries over the period between the late 1960's and the late 1990's; the countries are Belgium, France, Germany, Italy, the Netherlands, and the United Kingdom. The methods employed to obtain the measures make use of forecast-based decompositions of output into permanent and transitory components. The novelty of the measures presented in this paper is that they make use of actual output data and direct measures of expected output levels as provided in Business Surveys. In each country, the two series constitute separate sources of information on current and future output levels. The actual and expected output series can be modelled in the context of a multisectoral Vector Autoregressive (VAR) subject to innovations which reflect the arrival of news about current and (expected) future output levels. Various forecast-based decompositions can be obtained using the VAR models estimated for each country. These provide alternative measures of trend output based on forecasts of output levels at different forecast horizons and making use of the news in different ways.

The analysis relies on the availability of quantitative measures of expected output levels. These are derived from the qualitative information on output expectations provided by Business Surveys conducted in the six countries and published by the Directorate Gen-

[1] See the discussions in Stock and Watson (1989), Plosser (1989) and McCallum (1989), among others.

eral for Economic and Financial Affairs of the Commission of the European Communities.[2] The derivation of the expected output series is based on the procedure described in Lee (1994) in which measurement errors are taken into account using survey responses on future expectations and on outcomes which have been realised in the past. Having obtained direct observations on expected output, it is possible to investigate empirically the nature of expectations formation, including its rationality. It is also possible to consider the role played by expectations in the dynamic evolution of output without recourse to any (possibly ad hoc) assumptions on the underlying behavioural model of output determination and without use of a (possibly contentious) structural econometric model.

The use of forecast-based decompositions to identify the trend and cyclical components of output is arbitrary.[3] However, when Survey data are used, forecasts of output levels at some future time horizon are not only based on the most up-to-date information available on the output levels. They also take into account agents' knowledge on those parts of recent output movements which are unsustainable or which are known to reflect transitory adjustments to equilibrium. The forecast-based measures of trend output considered in this paper make use of this knowledge, as reflected in Survey responses, in different ways.

The plan of the remainder of the paper is as follows. In Section 2, we present the modelling framework and define the alternative measures of trend output which we believe to be of interest. In Section 3, we provide an overview of the data for the six countries, concentrating on the derivation of quantitative series on expected outputs and a description of their properties, including tests for rationality in expectation formation. In Section 4, we present the estimated VAR models of actual and expected outputs in the six countries and discuss the trend output series obtained.[4] Section 5 concludes.

[2] Details are provided in the Data Appendix.

[3] Alternative econometric methods employed to separate output into trend and cycles are discussed in Harvey (1985), Watson (1986), Evans (1989), Stock and Watson (1989), Evans and Reichlin (1994), and Kuttner (1994), for example.

[4] The derived series are available at http://www.le.ac.uk/economics/kcl2/.

2 Measuring trend output using a VAR model of expected and actual outputs

2.1 The modelling framework

For each country, we shall model the process simultaneously determining (the logarithm of) actual output, denoted y_t at time t, and (the logarithm of) measured expected output, where (the logarithm of) the expectation of output at time t, formed by agents on the basis of information available to them at time $t-1$, is denoted y_t^*. We assume that actual output is first-difference stationary, and that expectational errors are stationary; the first of these assumptions is supported by considerable empirical evidence, and the latter assumption is consistent with a wide variety of hypotheses on the expectations formation process, including the Rational Expectations hypothesis (REH).[5] Under these assumptions, actual and expected output growth have the following fundamental Wold representation:

$$\begin{bmatrix} y_t - y_{t-1} \\ y_{t+1}^* - y_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + A(L) \begin{bmatrix} \varepsilon_t \\ \nu_t \end{bmatrix}. \tag{2.1}$$

Here, α_1 is mean output growth, α_2 is mean expected output growth, $A(L) = \sum_{j=0}^{\infty} A_j(L)$, where the $\{A_j\}$ are 2×2 matrices of parameters, assumed to be absolutely summable, and L is the lag-operator. Also, ε_t and ν_t are mean zero, stationary innovations, with non-singular covariance matrix $\Omega = (\omega_{jk})$, $j,k = 1,2$. Both actual output growth at time t and the growth in output expected to occur in time $t+1$, based on information at time t, are determined at time t; the actual and expected mean growth rate are provided by the deterministic component $\alpha = (\alpha_1, \alpha_2)'$, where $\alpha_1 = \alpha_2$ if there is no bias in expectations, and the random innovations at time t are represented by the vector $v_t = (\varepsilon_t, \nu_t)'$.

Note that the error term ε_t is naturally interpreted as "news on output growth in time t becoming available at time t", while ν_t is "news on output growth expected in time $t+1$ becoming available at time t". Both types of news are important in the simultaneous determination of actual and expected output growth; interdependencies in their joint determination are accommodated directly in (2.1) through the lag filter $A(L)$ and indirectly

[5] Expected growth in output at time $t+1$, $y_{t+1}^* - y_t$, is also stationary, therefore, since it can be decomposed into actual output growth $(y_{t+1} - y_t)$ and expectational error $(y_{t+1}^* - y_{t+1})$:

through the covariance matrix Ψ. The model therefore incorporates the direct effects of news on actual and expected output growth, and the influences of feedbacks which exist in the determination of expected future output growth and actual output growth.

The general model in (2.1) can be expressed in a variety of different ways. For example, assume that $A^{-1}(L)$ can be approximated by the lag polynomial $A^{-1}(L) = B_0 + B_1L + \ldots + B_{p-1}L^{p-1}$, where $B_0 = I_2$ without loss of generality. In this case, (2.1) can be rewritten to obtain the AR representation

$$\begin{bmatrix} y_t - y_{t-1} \\ y^*_{t+1} - y_t \end{bmatrix} = A^{-1}(1)\alpha - B_1 \begin{bmatrix} y_{t-1} - y_{t-2} \\ y^*_t - y_{t-1} \end{bmatrix} - \ldots - B_{p-1} \begin{bmatrix} y_{t-p+1} - y_{t-p} \\ y^*_{t-p+2} - y_{t-p+1} \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ \xi_t \end{bmatrix} \tag{2.2}$$

and hence

$$\begin{bmatrix} y_t \\ y^*_{t+1} \end{bmatrix} = a + \Phi_1 \begin{bmatrix} y_{t-1} \\ y^*_t \end{bmatrix} + \Phi_2 \begin{bmatrix} y_{t-2} \\ y^*_{t-1} \end{bmatrix} + \ldots + \Phi_p \begin{bmatrix} y_{t-p} \\ y^*_{t-p+1} \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ \eta_t \end{bmatrix}, \tag{2.3}$$

where $a = M_0^{-1}A^{-1}(1)\alpha$; $\Phi_j = M_0^{-1}M_j$, $j = 1, \ldots, p$; and

$$M_0 = \begin{bmatrix} 1 & 0 \\ -1 & 1 \end{bmatrix};\ M_p = B_{p-1}\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix};\ \text{and } M_j = B_{j-1}\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} - B_j\begin{bmatrix} 1 & 0 \\ -1 & 1 \end{bmatrix};$$

for $j = 1, \ldots, p-1$. The error terms $u_t = (\varepsilon_t, \eta_t)'$ are defined by

$$\begin{bmatrix} \varepsilon_t \\ \eta_t \end{bmatrix} = M_0^{-1}\begin{bmatrix} \varepsilon_t \\ \xi_t \end{bmatrix} = \begin{bmatrix} \varepsilon_t \\ \varepsilon_t + \xi_t \end{bmatrix},$$

and the covariance matrix of the u_t is denoted $\Sigma = (\sigma_{jk})$; $j, k = 1, 2$; where $\sigma_{11} = \psi_{11}$; $\sigma_{21} = \psi_{11} + \psi_{12}$; and $\sigma_{22} = \psi_{11} + 2\psi_{12} + \psi_{22}$. Note that ε_t has the interpretation of "news on output level in time t becoming available at time t", which is equivalent to news on output growth given that y_{t-1} is known. On the other hand, η_t is interpreted as "news on the level of output expected in time $t+1$ becoming available at time t" which causes expectations of output in time $t+1$ to be revised. This type of news encompasses the news on output levels at time t and the news on growth expected to be experienced over the coming period ($\eta_t = \varepsilon_t + \xi_t$). In this sense, the news conveyed by η_t dominates that conveyed by ε_t.

Manipulation of (2.3) also provides the VECM representation

$$\begin{bmatrix} \Delta y_t \\ \Delta y^*_{t+1} \end{bmatrix} = a + \Pi \begin{bmatrix} y_{t-1} \\ y^*_t \end{bmatrix} + \sum_{j=1}^{p-1} \Gamma_j \begin{bmatrix} \Delta y_{t-j} \\ \Delta y^*_{t-j+1} \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ \eta_t \end{bmatrix}; \qquad (2.4)$$

where $\Delta = (1 - L)$ is the difference operator, $\Phi_1 = I_2 + \Pi + \Gamma_1$; $\Phi_i = \Gamma_i - \Gamma_{i-1}$; $i = 2, 3, ..., p - 1$, and $\Phi_p = -\Gamma_{p-1}$. Given the form of the Φ_i described in (2.3), it is easily shown that Π takes the form

$$\Pi = \begin{bmatrix} -k_1 & k_1 \\ -k_2 & k_2 \end{bmatrix} = \begin{bmatrix} -k_1 \\ -k_2 \end{bmatrix} \begin{bmatrix} 1 & -1 \end{bmatrix};$$

where k_1 and k_2 are scalars dependent on the elements of the B_j, $j = 0, 1, ..., p - 1$. Hence, the model at (2.1) can be written in a VECM form where $\Pi = \alpha\beta'$ and $\alpha' = [-k_1; -k_2]$ contains the parameters determining the speed of adjustment to equilibrium and $\beta' = [1; -1]$ is the cointegrating vector. The form of the cointegrating vector captures the fact that actual and expected output cannot diverge indefinitely and is incorporated through the inclusion of the error correction term $\beta'[y_{t-1}; y^*_t]' = y_{t-1} - y^*_t$. This property holds because expectational errors are taken to be stationary in this model, so that actual and expected output levels are cointegrated by assumption.

A final alternative for describing the model is the MA representation obtained through recursive substitution of (2.3):

$$\begin{bmatrix} \Delta y_t \\ \Delta y^*_{t+1} \end{bmatrix} = b + C(L) \begin{bmatrix} \varepsilon_t \\ \eta_t \end{bmatrix}; \qquad (2.5)$$

where $b = C(1)a$, $C(L) = \sum_{j=0}^{\infty} C_j(L)$, $C_0 = I_2$; $C_1 = \Phi_1 - I_2$ and $C_i = \sum_{j=0}^{p} C_{i-j}\Phi_j$, $i > 1$, $C_i = 0$, $i < 0$. As is well known, following Engle and Granger (1987), the presence of a cointegrating relationship between the y_t and y^*_t imposes restrictions on the parameters of $C(L)$; namely, $\beta' C(1) = 0$. Further, given that $\beta' = [1; -1]$, this ensures that $C(1)$ takes the form

$$C(1) = \begin{bmatrix} k_3 & k_4 \\ k_3 & k_4 \end{bmatrix} \qquad (2.6)$$

for scalars k_3 and k_4.

Although the error terms ε_t and η_t have a natural interpretation in terms of news becoming available at time t, the MA representation given in (2.5) is not unique. Given the dominance of the news incorporated in η_t, we might be interested in identifying the entire effect of this shock, taking into account the interdependencies which are known to exist between the two types of news arriving at time t. If we assume that ε_t and η_t are joint normally distributed, with covariance matrix $\Omega = (\sigma_{jk})$; $j,k = 1,2$; then we can write $\varepsilon_t = \rho\eta_t + \upsilon_t$ where $\rho = \frac{\sigma_{21}}{\sigma_{22}}$ and υ_t is orthogonal to η_t. An alternative MA representation which is of interest is then given by

$$\begin{aligned} \begin{bmatrix} \Delta y_t \\ \Delta y^*_{t+1} \end{bmatrix} &= b + C(L)\begin{bmatrix} 1 & \rho \\ 0 & 1 \end{bmatrix}\begin{bmatrix} \upsilon_t \\ \eta_t \end{bmatrix} \\ &= b + \tilde{C}(L)\begin{bmatrix} \upsilon_t \\ \eta_t \end{bmatrix}, \end{aligned} \tag{2.7}$$

where $\tilde{C}(L) = C(L)P$ and $P = \begin{bmatrix} 1 & \rho \\ 0 & 1 \end{bmatrix}$ and the covariance matrix of $\tilde{u}_t = [\upsilon_t, \eta_t]'$ is diagonal.

The model at (2.1), and the equivalent forms in (2.2), (2.3), (2.4), (2.5) and (2.7), is quite general and has no implications for the expectations formation process. However, the assumption that expectations are formed rationally can be accommodated in the model through the imposition of restrictions. If expectations are formed rationally, the expression for y^*_t given in (the second row of) the lagged version of (2.3) is equal to the mathematical expectation of the expression for y_t given in (the first row of) (2.3). Equating coefficients on the corresponding terms provides the REH restrictions:

$$\text{first row of } \Phi_1 = \begin{pmatrix} 0 & 1 \end{pmatrix}; \qquad \text{first row of } \Phi_j = \begin{pmatrix} 0 & 0 \end{pmatrix}, \qquad j = 2, \ldots, p; \tag{2.8}$$

or, equivalently, imposing these restrictions in (2.3),[6]

$$y_t = y^*_t + \varepsilon_t. \tag{2.9}$$

[6] Equivalently, in the error correction form of (2.4), the first row of $\Pi = \begin{pmatrix} -1 & 1 \end{pmatrix}$, so that $k_1 = 1$, and $\Gamma_j = \begin{pmatrix} 0 & 0 \end{pmatrix}$, $j = 1, \ldots, p-1$. A similar approach to the rationality in expectations is explored in Engsted (1991).

Hence, the deviation of actual output at time t from the level expected in the previous period is equal to the news on the output level becoming available at that time. This news is, by definition, orthogonal to information available at time $t-1$.

2.2 Measuring trend output

Having discussed the various alternative forms of the model of actual and expected outputs that are available, three alternative measures of trend output follow relatively naturally. The first is based around (a multivariate version of) the decomposition procedure introduced by Beveridge and Nelson (1981), hereafter denoted BN. This decomposition is applicable to models of (vectors of) variables which need to be differenced in order to achieve stationarity and presents the variable(s) as the sum of a stochastic trend, captured by a random walk with drift, and a stationary component. There is considerable evidence to support the view that output is difference stationary so that this decomposition is applicable here. The trend here is the expectation of the limiting value of the forecast of y_t conditional on time t information, or the "long forecast"; i.e. $\lim_{s\to\infty} E[y_{t+s} \mid I_t]$; where $I_t = \{\varepsilon_t; \eta_t; \varepsilon_{t-1}; \eta_{t-1}; \ldots\}$ is the information set at time t. The trend considers the effect of a (system-wide) shock to the two variables in the model at the infinite horizon; effectively, it abstracts from the cyclical effects of the shocks by concentrating on the infinite horizon only. Defining $C_0^* = C_0 - C(1)$ and $C_j^* = C_j + C_{j-1}^*$, $j > 0$; we can write $C(L) = \sum_{j=0}^{\infty} C_j L^j = C(1) + (1-L)C^*(L)$. The model given in (2.5) can then be written

$$\begin{bmatrix} y_t \\ y_{t+1}^* \end{bmatrix} = \mu_t + \tau_t; \tag{2.10}$$

where μ_t and τ_t are, respectively, the stochastic trend and cyclical components obtained through the BN decomposition, defined by

$$\mu_t = \mu_{t-1} + b + C(1)u_t \quad \text{and} \quad \tau_t = \sum_{i=0}^{\infty} C_i^* u_{t-i}.$$

Empirically, having obtained estimates of the parameters of $C(L)$ and measures of the u_t; the 'long run trend in output' is defined by

$$\begin{aligned} \bar{y}_t^L &= \begin{bmatrix} 0 & 1 \end{bmatrix} \mu_t \\ &= \begin{bmatrix} 0 & 1 \end{bmatrix} \left(\begin{bmatrix} y_t \\ y^*_{t+1} \end{bmatrix} - \sum_{i=0}^{\infty} C^*_i u_{t-i} \right). \end{aligned} \tag{2.11}$$

In (2.11), we have chosen to look at the long forecast of y^*_{t+1}, as opposed to that of y_t. However, given the cointegrating relation that exists between the variables, there is a single, common stochastic trend which evolves over time depending on the value of $C(1)u_t$; i.e., from (2.6),

$$C(1)u_t = \begin{bmatrix} k_3 & k_4 \\ k_3 & k_4 \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ \eta_t \end{bmatrix} = \begin{bmatrix} k_3\varepsilon_t + k_4\eta_t \\ k_3\varepsilon_t + k_4\eta_t \end{bmatrix}.$$

Hence, it is clear that the long forecast of y^*_{t+1} and y_t are equivalent in this case.

The meaning of the 'long forecast' is quite straightforward, and its advantages as a measure of the trend output level arise from the way in which it abstracts from cyclical movements by focusing on the long run only. Recognising the advantages of using forecasts of future output levels in defining trend output, and given that, under the REH, we have

$$y_{t+1} = y^*_{t+1} + \varepsilon_{t+1} \quad \text{and} \quad E[y_{t+1} \mid I_t] = y^*_{t+1},$$

so that an obvious alternative measure is provided by

$$\bar{y}_t^S = y^*_{t+1}. \tag{2.12}$$

This measure considers the forecast of output one period ahead based on information at time t; the "short forecast". The measure has the advantage over the long forecast that it is more directly focused on underlying economic activity at the current time. Perhaps more importantly, however, the model at (2.3) shows that this measure depends on η_t but not (directly) on ε_t. We have already noted that the news content of η_t dominates that of ε_t in the sense that the former contains information on output levels at time $t+1$, and therefore subsumes information on output at time t. In expressing their opinion on output levels in $t+1$, respondents are explicitly taking into account movements in ε_t and, in particular, any knowledge that they have on the 'unsustainable' component of ε_t (which influences their view on output growth in $t+1$). The trend series $\bar{y}^S_t$ smooths out the effects of shocks to the actual and expected output series to the extent that some part of current output movements are considered unsustainable.

A third, intermediate measure of trend output attempts to incorporate the advantages of the measures based on the short and long forecasts. This measure focuses on the infinite horizon effect of shocks, but it attempts to abstract from the effects of shocks which survey respondents consider to be unsustainable. To motivate the measure, we note first from (2.7) that

$$C(1)u_t = \tilde{C}(1)\tilde{e}_t = \begin{bmatrix} k_3 & k_4 \\ k_3 & k_4 \end{bmatrix} \begin{bmatrix} 1 & \rho \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \psi_t \\ \eta_t \end{bmatrix} = \begin{bmatrix} k_3\psi_t + (k_4 + \rho k_3)\eta_t \\ k_3\psi_t + (k_4 + \rho k_3)\eta_t \end{bmatrix};$$

so that the long run trend in output underlying $\bar{y}^L_t$ in (2.11) can be expressed equivalently in terms of the elements of u_t or $\tilde{e}_t$. The innovations ψ_t have been constructed to be orthogonal to the η_t and are associated with the unsustainable part of news on y_t which respondents discount in forming their expectations on output levels in time $t+1$. Of course, contemporaneous movements in output are not entirely unsustainable, and that part of news on y_t which is associated with a sustained effect (and correlated with η_t therefore) is acknowledged to have an effect on y_t and y^*_{t+1} through the $\rho\eta_t$ term. The complete effect of the innovations η_t on the long run forecast of actual and expected output levels are captured in the composite term $(k_4 + \rho k_3)\eta_t$. The proposed third measure allows for the feedbacks between actual and expected outputs over the (infinite) forecast horizon, but allocates the dynamic effects of the unsustainable innovations ψ_t to the cyclical component. Hence, we have

$$\Delta\bar{y}^M_t = \Delta\bar{y}^L_t - k_3\psi_t. \tag{2.13}$$

This measure corresponds to the unique decomposition of y^*_{t+1} into orthogonal permanent and transitory components discussed in Quah (1992), where 'orthogonality' here means that $\Delta\mu_t$ is uncorrelated with τ_t at all leads and lags.[7]. Such a decomposition was

[7] Clearly, neither Δy^*_{t+1} nor Δy_t are Granger causally prior to the other; under REH, for example, it

employed in Blanchard and Quah (1989) and has been widely used since that paper.[8] The orthogonality restrictions used in these decompositions are typically motivated by a behavioural economic model. However, while these behavioural models are usually not uncontentious, the discussion above indicates that the orthogonality restriction used in this paper has a relatively firm basis; here the transitory component is associated with that part of news on y_t arriving at time t which is revealed to be discounted by survey respondents as having an unsustainable effect on output.

Discussion in the literature of the choice between alternative decompositions has focused on the size of the trend and cycle. For example, Quah (1992) noted that there are an infinite number of decompositions available and that, in general, a decomposition can be chosen such that the trend is arbitrarily smooth (i.e. the variance of increments in the permanent component can be infinitely close to zero). If attention is restricted to MA representations, however, then there is a minimum bound for this variance and this minimum falls towards zero as the order of the MA process increases. In this sense, the BN decomposition (which defines the permanent component as a random walk) will maximise the variance of the permanent component. Evans and Reichlin (1994) establish that a multivariate version of the BN decomposition generates a smoother permanent component compared to the permanent component obtained applying the BN decomposition to a univariate model.[9] This result matches that of Quah (1992) since the extra information provided by the multivariate VAR effectively provides for a more complicated dynamic specification and this is equivalent to extending the order of the MA representation in a univariate model. Here, in this paper, comparison of the decompositions based on the multivariate model shows that growth in $\bar{y}_t^M$ must have lower variance than growth in $\bar{y}_t^L$

is apparent from (2.8) that Δy_t^* helps in the forecast of Δy_t, and it is unlikely that lagged values of Δy_t provide no explanatory power in forecasting Δy_{t+1}^* beyond that provided by lags of Δy_{t+1}^* itself. Theorem 4.1 of Quah (1992) establishes that in these circumstances, there exists an orthogonal decomposition of either of the integrated series and that this decomposition is unique.

[8] Recent examples of studies applying the Blanchard and Quah decompostion include Enders and Lee (1997) and Keating and Nye (1998, 1999).

[9] In what follows, we shall denote the permanent component of output obtained by applying the BN decomposition to a univariate model of actual output growth series by $\bar{y}_t$ and that obtained by applying the BN decomposition to a univariate model of our expected output growth series by $\bar{y}_t^*$.

as the former abstracts from the effects of (orthogonal) υ_t: Under the REH, actual output growth is decomposed into an anticipated element and an (orthogonal) unanticipated element, so that $\mathrm{var}(\Delta y_t) > \mathrm{var}(\Delta y_t^*)$. However, we cannot rank according to size the variance of growth in the corresponding trend measures, $\overline{y}_t$ and $\overline{y}_t^*$ (i.e. those obtained from univariate models of the two variables considered individually). Hence, we know that

$$\{\mathrm{var}(\Delta \overline{y}_t) \text{ and } \mathrm{var}(\Delta \overline{y}_t^*)\} > \mathrm{var}(\Delta \overline{y}_t^L) > \mathrm{var}(\Delta \overline{y}_t^M)$$

but we cannot enter $\mathrm{var}(\Delta \overline{y}_t^S)$ in the rank ordering.

While the relative smoothness of a trend output series is clearly of interest, the choice of the measure of trend output should depend on the use to which it will be put and the measure should be judged according to its relevance to its purpose rather than on its size or statistical properties. The use of a trend output measure is sometimes motivated by the desire to abstract from the noisy, uninformative part of output movements and sometimes from the complex adjustment dynamics generated as decision-makers continue to react to innovations over an extended period (so that their effects accumulate or iterate over time). Frequently, it is not possible to distinguish between the 'pure noise' element and the 'adjustment dynamics' although here, in this paper, we do have some information if we interpret the υ_t as the pure noise element. The different forecast-based measures of trends discussed above can be viewed as placing different emphases on these two desirable features. Hence, the trend measure $\overline{y}_t^S$, obtained using contemporaneous survey data only, places emphasis on eliminating the pure 'noise' element of output growth and makes no accommodation for adjustment dynamics. The measure $\overline{y}_t^*$ provides a long forecast, based on the BN of a univariate representation of the survey data, which abstracts from pure noise (by using only the survey data) but which also attempts to abstract from the cyclical adjustment by focusing on the infinite horizon effects of innovations. The measure $\overline{y}_t^M$ has similar advantages but, being based on a bivariate model of actual and expected outputs, it is able to capture some part of the adjustment delays directly by accommodating the effects of news of a (sustainable) shock both at time t (namely, $\rho\eta_t$) and at time t + 1 (a further η_t). The measure $\overline{y}_t^L$ focuses entirely on abstracting from the adjustment cycles, making use of the information on the unsustainable element of output innovations only to the extent that this can help to obtain a more complicated dynamic model specification for output growth. All of the trend output measures based on the BN decomposition provide a measure of trend output with the interpretation of a "normal" output level to which the economy will converge in the absence of any further innovations. The associated cyclical element represents the output growth in excess of normal rates observed as the economy returns to normal.

3 Analysing qualitative survey data in six European countries

In this section, we first discuss the general method by which directly observed measures of expectations of variables are obtained from survey data. Then, in Section 3.2, we apply the methods to Survey data for our six European countries and describe the properties of the expectations series that are derived.

3.1 Deriving series on output expectations from Surveys

The measurement of expectations based on surveys is complicated by the fact that surveys typically provide only qualitative data on expected events which have to be converted to a quantitative series. For example, in the Surveys that we employ here, information is provided on the proportion of respondents in the Survey who report that they expect the volume of their output to "rise", "stay the same", or "fall" over a given future period. The Survey also provides the equivalent information on what respondents report actually happened to output volumes over a given period in the past. Various conversion procedures have been proposed in the literature for converting the qualitative data to quantitative series,[10] but all procedures suffer from the problem that series derived from the qualitative data provide imperfect measures of the true series, and that the form of the conversion error contained in the derived series is unknown.

Lee (1994) describes a procedure to obtain a quantitative expectations series from the Survey responses which takes into account the presence of conversion error by using the forward-looking responses and the backward-looking responses obtained in the Survey

[10] Pesaran (1987) and McAleer and Smith (1995) provide discussions of various alternative conversion procedures and their relative merits.

in a particular way. Briefly, the procedure focuses first on the backward-looking survey responses and derives a measure of `realised' output growth over the previous period by applying any one of the available conversion procedures to the qualitative data. Conversion error is measured by the gap between this derived `realised' output growth measure and the output growth which was actually observed. Any systematic patterns in the conversion error are identified through a regression model in which the conversion error at time t is regressed on a vector of specified variables dated at time $t-1$ and before, denoted h_{t-1}. Next, the conversion procedure that was applied to the backward-looking survey responses is applied to the forward-looking survey responses to produce a quantitative series on expected output; this is denoted y_t^e and differs from the true expectations series, y_t^{α}, if conversion error is present. The procedure of Lee (1994) assumes that the conversion error contained in the measure y_t^e is of the same form as that contained in the backward-looking series and, on this assumption, the derived expectations series can be `purged' of conversion error using the regression results. The discrepancy between this purged measure of expected growth and observed growth can be interpreted as pure `expectational' error and the expectation formation process can be examined directly by analysing these expectational errors.[11]

3.2 Expected output series for six European countries

The empirical work of the paper investigates the survey responses given by samples of firms in the manufacturing sectors of six European countries. The countries are Belgium, France, Germany, Italy, the Netherlands and the UK and these were selected on the basis of data availability. The survey questions in every country refer to the respondent firm's own past and future, seasonally-adjusted output levels,[12] although the time horizon specified in the survey questions differ across countries. Hence, for Belgium, Germany, Italy and the Netherlands, the backward-looking part of the question refers to output

[11] For example, rationality requires these expectational errors to be orthogonal to known information.

[12] For example, for the UK, the responses relate to the question "Excluding seasonal variation, what has been the trend over the past four months, and what are the expected trends over the next four months, with regard to the volume of output?".

trends over the past month, while the question considers the last three months for France and the last four months for the UK. For all countries except UK, the forward-looking question refers to the next three months; for the UK, the specified time horizon is the next four months. All the surveys are conducted monthly, but the empirical work is conducted using quarterly data to match the time horizon over which survey respondents are typically asked to form their expectations.[13] The sample period mainly runs from the late 1960's to the late 1990's, although these also differ across countries: data for Belgium, Germany, and Italy are available over 1968q1-1998q1; France covers 1969q1-1998q1; the Netherlands covers 1972q1-1998q1; and the UK data period is 1975q3-1998q2.

The method chosen for converting the qualitative survey responses into quantitative series is the widely-used 'Probability Method'; the application of this method to the backward-looking and forward-looking survey responses provided the 'realised' output growth series and the (unpurged) expected output growth series, $y_t^e - y_{t-1}$; respectively.[14] Where the backward-looking survey responses relate to a one month period, a monthly realised series was derived, using all of the monthly surveys, and monthly conversion errors were obtained by comparing the realised series with actual monthly data. A quarterly conversion error series was then obtained by averaging the monthly error over successive three month intervals. The vector of specified variables (dated at quarterly intervals), h_{t-1}, which is assumed to be known to agents at time t, and which is used in the regression explaining the backward-looking conversion error, includes: a lagged dependent variable; up to four lags of manufacturing output growth; two lags of the interest rate; and two lags

[13] Hence, for the forward-looking expectations series, the analysis considers only the survey reponses published in January, April, July and October of each year.

[14] The Probability Method is described in detail in Pesaran (1987), for example. The method requires an assumption to be made on the form of the underlying subjective probability distribution of firms' future output change and the construction of a scaling parameter. In this work, the distribution is assumed to be normal and the scaling parameter is given by the ratio of the sum of the absolute changes in actual output to the sum of the absolute values of the unscaled expected output series derived from the survey data. This form for the scaling parameter is appropriate because growth rates are observed which are positive, negative and close to zero (although the subsequent analysis is unaffected by the use of alternative scaling parameters).

of the exchange rate of each respective country.[15] A specification search was undertaken to obtain a well-specified model of the conversion error for each country,[16] and these were then used to construct expected output growth series, $y_t^* - y_{t-1}$ which are purged of conversion error under the assumptions, and employing the method, described in Section 3.1 above.

Table 1 presents summary statistics of the properties of the actual and expected output growth series derived from the Survey data and Figures 1a-1f show plots of these series for each country. The first two columns of Table 1 present Augmented Dickey-Fuller (ADF) statistics calculated to investigate the order of integration of the actual output data.[17] The unit root hypothesis cannot be rejected when applied to the (log) output data (y_t), but is comprehensively rejected when applied to the output growth data (Δy_t). These results confirm that Manufacturing Sector output can be considered an I(1) process, as assumed in the analysis of Section 2. The third column provides the mean (quarterly) growth rates of Manufacturing Sector output in the six countries during their respective sample periods and shows the wide variety of rates experienced across the countries over the last two decades.

There follows two sets of statistics in Table 1 relating to the (unpurged) derived expectations series, $y_t^e - y_{t-1}$, and the purged series, $y_t^* - y_{t-1}$. In these, we find first that contemporaneous correlations between actual output growth and the unpurged expected output growth series are positive in all countries, but small in most cases, averaging 0.2437. In comparison, contemporaneous correlations between the actual and the 'purged' expected output growth series are positive and larger for each of the countries, averaging 0.4136. Second, the reported ADF statistics indicate that a hypothesised unit root in the expectational errors can be rejected for both expectation series in all of the countries. Given that the actual output growth series have been shown to be I(0), this result implies

[15] The interest rate used is the discount rate, and the exchange rate is the average exchange rate of the country currency to the US Dollar over the quarter.

[16] Hence, we ensured that the 'backward-looking' regression model exhibited no serial correlation, parsimony, stability in the parameters, and satisfied optimal information criteria.

[17] The orders of augmentation were selected on the basis of the Akaike and Schwarz-Bayesian information criteria. No more than two lags were required for any of the countries.

that the actual and expected output series are both I(1) and cointegrated with cointegrating vector $(1\ -1)$. Third, the skewness statistic provides no evidence of asymmetries in the responsiveness of expectation formation to increases and decreases in output in either of the expectation series for any country. Fourth, the 'SC' statistics show that there is evidence of (first-order) autocorrelation present in the unexpected output growth series based on y_t^e in the UK, but there is no such evidence in the 'purged' expectational errors in any country. Finally, the 'H' statistics show that the expectational errors are strongly related to actual output growth in both series, with large errors made at times when output growth, in absolute terms, is relatively large. This reflects a 'conservatism' in expectation formation whereby the expected output growth series are less volatile, and have a lower variance, than the actual output growth series (as predicted by REH). This feature of the data is also clear in Figures 1a-f which illustrate the substantial variability in the countries' actual output growth series and the considerably less volatile purged expected output growth series.[18]

Finally in Table 1, statistics d1-d3 are presented to test the orthogonality of the various types of error to information which is known to agents in the industry when expectations are formed, h_{t-1}: In each case, the statistics are to be compared with the χ^2 distribution with six degrees of freedom.[19] The statistics denoted 'd1' test the orthogonality of the expectational errors based on y_t^e and effectively test the rationality of expectation formation under the assumption that expectational conversion errors are orthogonal to known information. This hypothesis is strongly rejected in all six EU economies. The statistic 'd2' provides the corresponding test of the hypothesis that the backward-looking conversion error is orthogonal to known information. These also provide strong evidence with which to reject the hypothesised orthogonality in all but one economy (the Netherlands). This indicates that an adequate treatment of the conversion errors is required before a test of rationality can be carried out, and certainly suggests that the 'd1' statistics should

[18] This observation is consistent with the conservatism in expectation formation described in Lee (1994) and Lee and Shields (1999)'s analysis of price, cost and output expectations in the industries within UK manufacturing.

[19] The reader is referred to Lee (1994) and Lee and Shields (1999) for further details of the test statistics.

be interpreted with caution. Finally, the statistics denoted 'd3' test the orthogonality of the expectational errors based on the 'purged' expectations series y_t^*, and therefore provide a test of the rationality of expectations formation under the assumption that the expectational conversion error is of the same form as the realisation conversion error. In this case there is no evidence with which to reject the hypothesised orthogonality in any country. Given that the assumptions underlying this final test of rationality are relatively weak, these results provide some support for the view that expectations on manufacturing output growth are formed rationally in our six countries.

4 Trend output measures in six European countries

In this section, we consider the various measures of trend output in conjunction with the estimated models that underlie the measures. Table 2 reports the estimated models of $\Delta y_t = y_t - y_{t-1}$ which are used in the construction of the trend measures $\bar{y}_t$ in each country. For the purpose of comparison, Table 3 reports the corresponding models of $\Delta y_t^* = y_t^* - y_{t-1}^*$: Table 4 presents parameter estimates of the second row of the bivariate VAR model given in (2.2) and this model is used in the construction of the trend measures $\bar{y}_t^S; \bar{y}_t^M$; and $\bar{y}_t^L$.[20] We shall argue that this bivariate model provides a more reliable basis on which to construct measures of trend output than the univariate model using actual output alone. Figures 2a-2f illustrate the role of the Survey data by presenting the trend output measures resulting from the univariate model of actual output ($\bar{y}_t$) and the bivariate VAR model of actual and expected output ($\bar{y}_t^L$), and compares these with the actual output series. Figures 3a-3f illustrate the alternative use of information contained in the actual and expected series and plot three of the alternative measures of trend output ($\bar{y}_t^S; \bar{y}_t^M$ and $\bar{y}_t^L$) against the actual output series for each of the six countries.

Table 2 reports the regression results which underlie the trend output measure $\bar{y}_t$ for the univariate model of actual output. The table shows that there are some important differences in the properties of the output growth series across the economies considered. While the short-run dynamics in output growth can be adequately captured by the inclu-

[20] Note that, in view of the support provided for REH in Table 1, the restricted parameters of the first row of the VAR expression (2.2) are provided by the REH restriction in (2.8).

sion of one or two lagged values of Δy_t in all countries, the differences in the parameter estimates show that these dynamics differ considerably across countries.[21] Moreover, the long run effects of shocks also vary across the six economies. $P_{\bar{y}}$ measures the size of the long run impact on actual output of a positive unit shock to actual output based on the estimated univariate model.[22] This measure ranges from 0.76 in Belgium and the Netherlands to 1.75 in the UK.[23] The differences in the measures of $P_{\bar{y}}$ across the countries means that the trend series $\bar{y}_t$ also have different properties. Specifically, as is clear from (2.10), any measure of the trend based on the BN decomposition is given by an accumulation of scaled estimated innovations, where the scaling depends on $P_{\bar{y}}$. Hence, estimates of $P_{\bar{y}}$ which are less than unity, indicating that an innovation causing output to rise by 1% on impact causes output to rise by less than 1% at the infinite horizon, will be associated with trended series $\bar{y}_t$ which are smoother than the actual series. Conversely, countries for which $P_{\bar{y}}$ exceeds unity will have a more volatile $\bar{y}_t$ series. Given the relatively simple univariate specification obtained to explain output growth in the six countries, the $P_{\bar{y}}$ are generally quite precisely determined. Despite this, however, it is clear that even quite small changes in parameter estimates might have a substantial effect on $P_{\bar{y}}$, and hence measured $\bar{y}_t$.[24]

Table 3 reports the corresponding parameter estimates from the univariate model of expected output growth, Δy_t^*. It is clear from the regression coefficients that the dynamics underlying expected output growth are quite different to those of actual output growth; in Belgium, for example, the model of Δy_t^* implies a relatively prolonged adjustment

[21] For parsimony, the reported regressions of Table 2 are the outcome of a specification search in which variables are excluded if they exhibit t-ratios less than unity in absolute value. The same search procedure is used in Tables 3 and 4 also.

[22] If the univariate AR(2) model of output growth is rewritten in its MA form $\Delta y_t = b + C(L)\varepsilon_t$; then $P_{\bar{y}} = C(1)$.

[23] Note that these measures relate to the persistence of shocks to the manufacturing sectors of the six countries and are therefore not directly comparable to the measures of Campbell and Mankiw (1989) or others who consider economy-wide output. However, the estimated figure for the UK is in line with that obtained for the manufacturing sector of the UK in Lee et al (1992).

[24] The sensitivity of persistence measures based on univariate models of international output growth to changes in model specification is discussed in Lee (1998).

of output to its new level following a positive shock when compared to the adjustment implied by the model of Δy_t and, in the UK, the model of Δy_t implies a relatively smooth, monotonic rise in output following a shock while the model of Δy_t^* implies a more rapid oscillating increase. However, in terms of the long run effects of shocks, we note that the rank ordering of the persistence measures $P_{\bar{y}}$ across countries is similar to that of $P_{\bar{y}^*}$.[25] This observation is, of course, compatible with the presence of the cointegrating relationship between y_t and y_t^* that we have already established, and the absence of this error correction term from the univariate models of Tables 2 and 3 represents a model misspecification. Moreover, the differences in the short run dynamics of the two sets of results relating to Δy_t and Δy_t^* also provides a priori support for the use of the bivariate model of y_t and y_t^* discussed in Section 2 and its more flexible dynamic specification.

Table 4 provides the parameter estimates for the bivariate VAR model given in (2.2) which can be used to derive the measures of trend output $\bar{y}_t^L$ and $\bar{y}_t^M$. When combined with the REH restriction of (2.8), the models of Table 4 provide a substantially more complicated dynamic specification than was, or could be, provided by any univariate model of (actual or expected) output. First, we know that, in combination with (2.8), the models of expected output growth, $y_{t+1}^* - y_t$, in Table 4, provide the estimated Vector Error Correction Model of (2.4) for each country, so that they incorporate the effects of the cointegrating relationships between y_t and y_t^* by construction. Second, up to two lagged values of expected output growth are found to be statistically significant in all countries' models, with additional actual output growth terms also contributing to the fit of the regressions in Belgium, Germany and Italy. And third, the estimated value of the ρ, reflecting the contemporaneous correlation between innovations in actual and expected future output included in each country's model, averages 0.75, signifying the importance of taking into account the simultaneity of the determination of actual and expected outputs. Taken together, these three arguments provide empirical support for the use of the bivariate model in preference to any univariate model both in terms of potential model misspecification and in terms of restricted dynamics.[26] It seems reasonable

[25] The $P_{\bar{y}^*}$ measures cannot be directly compared to $P_{\bar{y}}$ since $P_{\bar{y}^*}$ now relates to the size of the long run impact on expected output of a one percent shock to expected output.

[26] No attempt has been made to adjust the models for the effect of once-and-for-all events (such as

to argue that, on these grounds, the trend measures of output based on the model of actual and expected output are also to be preferred to those based on analyses of actual output considered alone.[27]

Having argued that the models of Table 4 provide a more reliable basis for the measure of trend output than those of Table 2, we now consider the differences between the measures $\bar{y}_t$ and $\bar{y}_t^L$ derived from these models. Figures 2a-2f show that the two measured series differ quite substantially in most countries. Given that both measures are based on the BN decomposition, a large part of these differences reflect differences in the measures of the persistence of shocks to output obtained from the models. In Table 4, $P_{\bar{y}^L}$ represents the size of the infinite horizon impact on actual output of a system-wide shock to actual and expected output that causes actual output to increase by one percent on impact, where the system is that of Section 2. The measure represents a multivariate version of the univariate persistence measures found in the literature and the measures of $P_{\bar{y}}$ from the univariate models of Table 2 are directly comparable with the $P_{\bar{y}^L}$.[28] Comparing $P_{\bar{y}}$ and $P_{\bar{y}^L}$, we find that, for all six countries, the measured persistent effect of shocks to trend output resulting from the bivariate model is higher (and considerably so for some countries) relative to the persistent effects of shocks to trend output derived from the univariate specification. For instance, in Belgium, France, Italy and the Netherlands, $P_{\bar{y}}$ is less than unity whereas in the bivariate model, the long run impact on actual output is estimated to be greater than one. Persistence in the models for Germany exceed unity in both Tables 2 and 4, although the estimate of $P_{\bar{y}}$ is considerably lower than $P_{\bar{y}^L}$: While

price shocks or national strikes) which result in outliers and which help explain some of the statistically significant diagnostic statistics in Tables 2 and 4. However, diagnostic statistics in Table 4 are generally acceptable and provide further support for this model over the univariate model of Table 2.

[27] It is worth stressing that this empirical argument matches that of Evans and Reichlin (1994) who promote the use of additional macroeconomic variables in conjunction with actual output in modelling trend output. However, because it relates to essentially the same economic magnitude, the use of expected output with actual output in a VAR model has the advantage that it provides the model with a parsimonious structure and it avoids the need to choose the relevant additional macroeconomic variables (on the basis of a possibly contentious structural model).

[28] For further details of measures of persistence in the context of a multivariate framework, see Pesaran, Pierse and Lee (1993).

the estimates of $P_{\bar{y}^L}$ are relatively imprecise in some cases, it appears that the additional dynamic sophistication of the bivariate model (including the effect of the feedbacks between actual and expected outputs captured by the error correction term) allows for a more prolonged effect of shocks and one in which the effects accumulate over time. In terms of the measures of output trends, this is reflected by more volatile trend series in four of the six countries than are observed using the univariate models of Table 2 (France and the UK being the exceptions).

Figures 3a-3f examine the alternative trend measures $\bar{y}_t^S$, $\bar{y}_t^M$ and $\bar{y}_t^L$, plotting these against the actual output series for each of the six countries. Recall that $\bar{y}_t^S$ is the 'short forecast', given by y_{t+1}^{π}, which focuses on the underlying activity in the economy at the current time. Figures 3a-3f show that this series fluctuates relatively closely around actual output in all countries, although the series highlights some important occasions during which actual and expected output diverge over protracted periods in most countries. In contrast, the measures $\bar{y}_t^L$ and $\bar{y}_t^M$ are both based on the BN decomposition applied to the bivariate models of Table 4 and show considerably more volatility than actual output levels in most cases. Recall that, from (2.13), $\bar{y}_t^M$ differs from $\bar{y}_t^L$ by the magnitude $-k_3\upsilon_t$, where υ_t is the 'unsustainable' part of innovations to output (in the sense that their effect is uncorrelated with innovations to the expected output level one period ahead). In Table 4, we provide estimates of k_3 and k_4 defined in expression (2.5) and based on the estimated parameters of the bivariate VAR model. As is clear from the Table, values of k_3 vary considerably across countries and this gives rise to the contrasting variations between $\bar{y}_t^L$ and $\bar{y}_t^M$ for each country. Indeed, in some countries and over some periods, the υ_t are of comparable size to the ε_t, so that their accumulated effect (reflected by the value of k_3) is quite substantial in some cases, and there are considerable differences between the measured trends given by $\bar{y}_t^M$ and $\bar{y}_t^L$.

Finally, in view of the interest expressed in the literature on the size of changes in the trend and cyclical components of output, Table 5 provides the statistic $R = var(\Delta\ cycle)/var(\Delta\ trend)$ for each of the measures of trend output in the six countries. This measures the ratio of the sample variance in the change in cycle to the sample variance in the change in trend output, and provides an indication of the smoothness of the different trend measures. According to the discussion in Section 2.2, we expect var($\Delta \bar{y}_t$) to exceed var($\Delta \bar{y}_t^L$) and, in turn, we expect var($\Delta \bar{y}_t^L$) to be greater than var($\Delta \bar{y}_t^M$). As it turns out, the lowest value of R is indeed that based on the $\bar{y}_t$ measure in all six countries reflecting the fact that most volatility is observed in the growth in this trend measure. The calculated R statistics based on $\bar{y}_t^M$ and $\bar{y}_t^L$ are broadly comparable, both being substantially larger than those based on $\bar{y}_t$; and reflecting the relative smoothness of the trend measures obtained from the bivariate model. In all cases, the highest value of R; and the least smooth trend, is that based on one period ahead forecasts $\bar{y}_t^S$:

5 Discussion

The primary purpose of this paper is to suggest some alternative measures of trend output based on a VAR model of actual and expected output series, where the latter is derived from Business Surveys. The VAR modelling framework that is described provides an economically-meaningful structure within which output growth can be analysed without relying on any (possibly contentious) behavioural economic assumptions. The structure helps identify innovations in the model with news of different types and provides an economic motivation for the alternative trend measures that are obtained on the basis of the VAR model.

The statistical analysis of the previous sections provides some important empirical insights in its own right, however. In particular, we find that the rationality of expectations formed on future output growth cannot be rejected in any of the six countries investigated. Further, although cointegrated with the actual output series, each country's expected output series demonstrates very different time series properties to the corresponding actual output series, and makes a significant and economically-substantive contribution to the estimated bivariate models of output growth in every country.

The VAR model of the joint determination of actual and expected output levels captures long-run and short-run dynamic features of the data which are not, and cannot be, captured through a time series analysis of the actual output series data considered alone. These differences show in the measures of trend output formulated using a univariate model of the actual output series taken alone or using the bivariate VAR model of the joint determination of actual and expectation series. In particular, measures of the persistent effects of shocks based on the bivariate model are larger than those based on the univariate model in all six countries considered in the paper. This means that the trend measures of output based on the bivariate model are far more responsive to shocks than the trend measures based on a univariate analysis. This is true both for the trend measure constructed using the 'typical' shocks impacting on actual and expected output, $\overline{y}_t^L$, and for the trend measure based on the orthogonalised, 'sustainable' shocks, $\overline{y}_t^M$, although these two measures also possess very different time series properties in most countries.

The alternative measures of trend output suggested in the paper have a number of desirable features. They are simple to construct, update readily to new information, and adjust stochastically in response to local variations. However, this is true for many decompositions. The particular advantage of the measures presented here is in their use of news on actual current and future expected output levels as it becomes available. The economic significance of these different types of news will vary according to circumstances, and the alternative measures of the trend proposed in the paper reflect this by placing different weight on the different types of news. Trend output measures are used in a wide variety of contexts and, generally speaking therefore, the proposed measures provide alternatives which will be relevant in different circumstances, depending on the purpose to which they will be put.

Of course, one important use of trend output measures is in structural macroeconometric models (e.g. macroeconomic models incorporating a Phillips curve type relationship in which inflation rises of falls according to the value of actual output levels relative to the trend level). There is considerable scope, therefore, in using the measured output trends, and associated output gaps, in conjunction with inflation measures or other macroeconomic magnitudes. Moreover, such an analysis can provide a further criterion for choosing between the alternative measures of trend output under the implicitly assumed structural model. This remains the subject of our own future research. However, it is hoped that the work of this paper informs and formalises the role of expectations in the dynamic evolution of output in the six economies considered, and will also provide measures of trend output which can be readily used and evaluated in other researchers' macroeconomic modelling work.

6 Data Appendix

The expectations data for Belgium, France, Germany, Italy and the Netherland has been obtained from two consecutive publications of the Directorate General for Economic and Financial Affairs of the Commission of the European Communities; namely, the Report of the Results of the Business Survey carried out among Heads of Enterprises in the Community, 1967-1975, and Results of the Business Survey carried out among Managements in the Community, 1976-1998. The survey question on production expectations has been published since 1967; the realised output survey data prior to 1980 was provided directly by the Commission of the European Communities. The expectations data for the UK has been taken from successive issues of the CBI's Survey of Industrial Trends. This Survey has been carried out since 1958, and published quarterly since 1972. However, the responses to the output volume question have been published since 1975q3; prior to that date, the question was phrased in terms of output values as opposed to output volumes.

The index of production for the Total Manufacturing industry for each country (except the UK) has been taken from successive issues of two consecutive OECD publications; Industrial Production, Quarterly Supplement to Main Economic Indicators, 1967-1978, and Indicators of Industrial Activity, 1979-1998. The output data for the UK has been taken from various issues of the CSO's Monthly Digest of Statistics. Seasonally-adjusted monthly output indices are used to calculate output growth rates, measured as the percentage change in the output index from its level in an earlier month where the period is chosen so that the time horizon matches that of the question posed in the corresponding Survey. An adjustment has been made to the data point in Germany for May 1984 when industrial disputes in Heavy Manufacturing sector lead to a large and unprecedented fall in the level of output. To adjust for this, we replaced the original observation by an average of the index of production for April and June.

Finally, the discount rates and exchange rates (defined as the average exchange rate of the country currency to the US Dollar) are obtained from DATASTREAM at monthly intervals, with growth rates being calculated as above.

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