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INTERIM EMPLOYMENT AND A LEADING INDICATOR FOR THE BELGIAN LABOUR MARKET

by

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Interim Employment and a Leading Indicator for the Belgian Labour Market

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ABSTRACT

This paper focuses on the construction of a leading indicator for the Belgian labour market based on labour market variables. It is shown that our employment indicator constructed from monthly data on interim work and business failures: (1) resembles quite well the cyclical pattern of observed employment in Belgium; (2) performs not significantly better when product market variables are added; (3) is a better predictor of the cycles in the labour market compared to existing leading indicators for the product market. Furthermore, it was found that even more accurate forecasts of future employment could be derived if information on the past behaviour of total employment (captured by an AR(2)-process) was added to our constructed leading indicator. But this last specification loses its leading character due to long publication delays for the employment data.

JEL classification: B41, E32

Keywords: business cycles; leading indicators; seasonal adjustment; detrending; interim employment

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1. Introduction

Most macroeconomic variables exhibit a similar cyclical pattern, representing the fluctuations in the aggregate level of economic activity, known as the business cycle. Because of timing differences, publication delays and other problems, it is however difficult to get a clear picture of the current and future state of the cycle based on these individual series. Therefore, a number of leading economic series are combined into a composite leading indicator. So far, most national as well as international institutes constructed only leading indicators for the product market. The aim of this paper is to construct a leading indicator for the Belgian labour market. The main purpose of this indicator is to predict the cyclical pattern, as well as the timing of the turning points in the employment series. This exercise is especially relevant for Belgium because this country lacks high-frequency (monthly or even quarterly) data on total employment. Furthermore, the yearly employment figures are published with an average lag of 12 months. As will be shown in this paper, it is possible to find some variables (quickly available at a monthly basis) which lead the actual pattern of total employment with at least 2 months, hence employment can be predicted minimum 14 months ahead.

The construction of our labour market indicator will be based on the standard OECD/NBER methodology of constructing composite leading indicators (OECD(1987b), Nilsson (1987)). But in contrast with other applications, we will concentrate on the labour market and hence experiment with the construction of an employment indicator using only labour market variables[1]. Monthly figures on business failures and the total number of hours worked via interim contracts will prove to be very successful as leading variables for total employment. Especially interim employment seems to be very sensitive to the business cycle, hence it can be assigned a keyrole in predicting the cycles in the labour market. This is not surprising, because in the presence of high hiring and firing costs[2] and uncertainty, firms often prefer to hire (initially) only interim workers in response to a positive product market shock. In case of a downturn, these temporary workers will be the first to be laid off.

[1] Because most shocks in the product market are propagated to the labour market, similar cycles can be expected. This, however, does not imply that product market variables are the most appropriate indicators for the labour market, because it is highly possible that the timing as well as the amplitude of the cyclical changes is very different.

[2] According to several indices constructed to rank countries in terms of labour market strictness, Belgium always appears at the top of countries with the most strict employment protection (see among others Emerson (1988), Grubb and Wells (1993)), OECD (1994)).

The paper is organised as follows. After the selection of the reference series and the potentially leading variables, an elaborate discussion is given of the consecutive steps required in order to identify the cyclical component of each selected series. These steps imply the elimination of seasonal, irregular and trend components. The next section describes how several cyclical components are aggregated into a composite leading indicator and how this indicator can be evaluated. In an extension, it will be tested whether adding a simple AR(2)-process to the leading indicator leads to any significant improvement in predicting the actual cycles in the labour market. Afterwards, a short section focuses on a composite leading indicator for predicting total unemployment, rather than employment. Finally, the last section concludes.

2. Constructing a leading indicator for the Belgian labour market

In this section a leading indicator for the Belgian labour market will be constructed by using labour market variables and following the OECD/NBER methodology (OECD(1987b), Nilsson (1987)). According to this methodology, the first step is to select a reference series and some leading indicators. Afterwards, the researcher has to identify the cyclical component of each of these indicators. The cycle is calculated by elimination of the seasonal, trend and irregular component and is expressed as deviation from the trend ("deviation-cycles"). Finally, these adjusted indicators are combined in a composite leading indicator.

2.1. Selection of the series

Because we will construct a leading indicator for the Belgian labour market, total employment in Belgium is the obvious reference series. The Ministry of Employment and Labour (Ministerie van Tewerkstelling en Arbeid) publishes data on this variable, but the main problem is that this is done only on a yearly frequency and is based on an estimation of the total employed population on 1 day (30th of June). The R.S.Z. (Rijksdienst voor Sociale Zekerheid), however, collects also quarterly data[3], but this covers only the employees in the private sector. Furthermore, this data is only available for the period 1993Q1-1997Q1 and published with a delay of 12 months. Because of these drawbacks, we will also experiment with unemployment as reference series. For

[3] This data is also based on an estimation of the employment at four particular days (31/3, 30/6, 30/9 and 31/12), rather than calculations of the labour volume (i.e. number of employed persons multiplied by the actual hours worked per person).

this variable, we use monthly figures from the R.V.A. (Rijksdienst voor Arbeidsvoorziening) for the period 1980:01-1997:12. Figure 1 and 2 visualise the evolution of these two reference series.

Figure 1: Number of employees in the private sector in Belgium

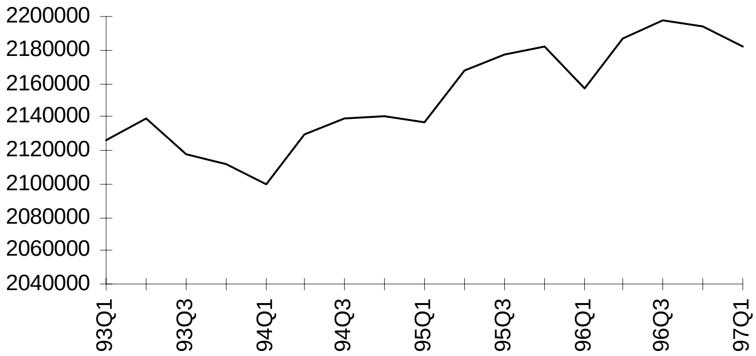
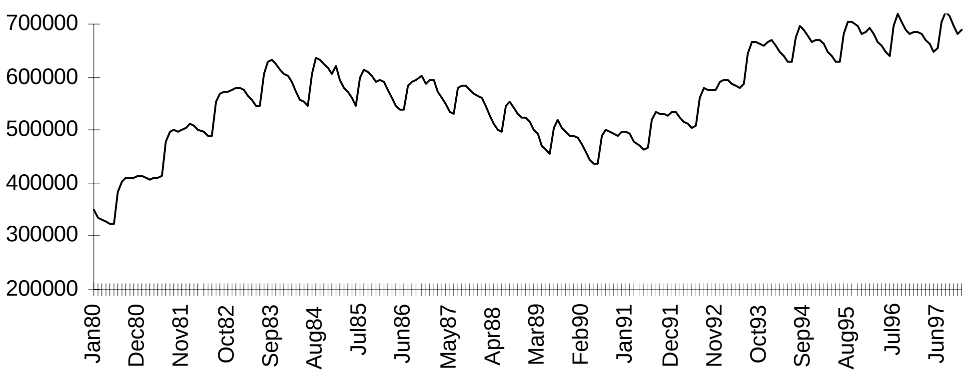


Figure 2: Number of unemployed persons in Belgium



The next step is to select economic variables whose cyclical movements typically predate those of the reference series. The top part of table D1 (see appendix D) gives an overview of the variables which can be used to construct a leading labour market indicator. Data on all these variables is quickly available and appears on a monthly basis.

2.2. Identification of the cyclical components of the series

In order to identify the cyclical component of the selected series, we need to decompose each series into a seasonal, trend, cyclical and irregular factor. These four components are in fact determined by the method of decomposition used because they are not observable in reality. Hence, it is important to state the definition and the explicit or implicit assumptions made about these components. A classic, but debatable, assumption is that it is possible to decompose each series into these four components and that these factors are independent of eachother. With respect to the functional relationship between these components it is often assumed that they are related either in an additive or in a multiplicative way.

1. Seasonal adjustment

The seasonal component is filtered out with the Census X-11 procedure developed by the US Bureau of the Census. This method can be applied to seasonalise both monthly and quarterly series, either via the additive or the multiplicative adjustment technique. Furthermore, Census X-11 has a special treatment for outliers[4] and trading-day effects[5]. A detailed description of the X-11 programme is given in appendix A. The main motivation for choosing this technique is that it is easily applicable on a large scale and does not require a large number of observations. In case of a limited number of series available for long time periods, one can also use model-based methods. They produce a specific adjustment procedure for each individual time series and can be classified in "error-components models" and "structural time series models". Error-components models assume that the observed series (Z_t) can be decomposed additively[6] into a seasonal component (S_t) and a non-seasonal[7] component (N_t), hence $Z_t = S_t + N_t$. Explicit statistical models (or spectral densities) are used for Z_t, S_t and N_t. The various methods belonging to this category differ in the type of model fit to the observed Z_t's and in the assumptions used in specifying models for S_t and N_t. The second category of model based approaches contains structural time series models (STM). In contrast with the error-composition models, a STM provides direct modelling of the three components (i.e. the trend-cycle, the seasonal and irregular component) and assumes that the entire structure of a time series model changes over the seasons, hence all components are stochastic. Parameter estimation can be done by using the Kalman filter (den Butter and Fase (1991)).

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[4] Census X-11 deals with extreme values through the use of "statistical control principles", that is values that are above or below a certain range (expressed in terms of multiples of the standard deviation) can be modified or dropped before final estimates for the seasonality are computed (U.S. Bureau of the Census (1967)).

[5] Trading-day effects arise because different months have different number of days and different number of trading-days (i.e. Mondays, Tuesdays, etc.). Census X-11 allows to test whether trading-day fluctuations exist in the series and if this is the case, it provides trading-day adjustment based on the actual variations in the data. Seven daily weights are estimated by regressing the irregular series upon the number of times each day of the week occurs in each particular month. From these seven weights, monthly factors are constructed and divided into the data to remove trading-day variation (U.S. Bureau of the Census (1967)).

[6] In case a multiplicative model is more appropriate, an additive decomposition can be used for the logarithms of the original series.

[7] It is also possible to isolate a trend (or trend-cycle) component from N_t.

In contrast with these model-based techniques, Census X-11 is a pure mechanical adjustment technique and lacks an underlying statistical model. Other disadvantages are its sensitivity to an extension of the data series and the fact that the method can only handle a seasonal pattern which is slowly changing over time. Nevertheless, this method also has some big advantages. At first, some authors (e.g. den Butter and Mourik (1990)) claim that Census X-11 is not entirely without a theoretical foundation because its reduced form is based on a (close approximation of a) special case of a structural time series model. Furthermore, it performs better than other mechanical methods and almost as good as methods bases on ARIMA models (den Butter and Fase (1991)). Other advantages are the multiple refinements for outliers, extreme values and different numbers of trading days which can be applied more than once, in order to obtain successively improved estimates of the components. Different tests and summary statistics make it possible to check whether seasonal adjustment is necessary and allow to test the quality of the decomposition. Finally, Census X-11 can pick up a gradual change in the seasonal pattern and in contrast with the model-based techniques it is more suitable for large-scale applications.

In our application it is assumed that the different components of all series, except unemployment[8], are related in a multiplicative way, hence the underlying model can be written as: $X_t = TC_t * S_t * TD_t * I_t$

where X_t is the original (observed) series; TC_t, S_t, TD_t and I_t are respectively the trend-cycle, seasonal, trading-day and irregular component. By means of example, we will present the main results of the multiplicative seasonal adjustment of one series, namely TOT (i.e. the total number of hours worked during 1 month by white and blue-collar interim workers). One of the summary statistics given by the programme indicates whether a stable seasonal pattern can be found in the original series. This stable seasonality test (F-test) consists of computing the ratio of the “between months” variance to the residual variance. If this F-ratio is above its critical value, a stable seasonal pattern is present. Along the same lines, the programme performs a moving seasonality test to discover a change in the seasonal pattern over time. Table 1 reports the outcomes of these two tests. From this, it is obvious that the TOT-series has a very

[8] Empirical evidence suggests that most economic time series show a proportional relationship between the seasonal and the trend-cycle component, hence multiplicative seasonal adjustment is required. But for series reflecting a balance (e.g. unemployment) it might be more appropriate to assume an additive model.

stable seasonal pattern, which shows no significant changes over the sample period. Hence, adjusting the series for seasonality was necessary[9].

Table 1: Results stable and moving seasonality test for TOT

	F-statistic	critical F-statistic (at 5% sign.level)
Stable Seasonality Test between months	27.367	1.97
Moving Seasonality Test between years	0.603	2.5

Figure E1 (see appendix E) visualises the decomposition of TOT into four components. There, the second graph shows a clear seasonal pattern in the series, i.e. the number of hours worked by interims is much higher in March, the summer-period (June, July, August and especially September) and December.

Applying this multiplicative (and the additive for unemployment) seasonal adjustment method, including the correction for trading-day variation, to all series presented in table D1 (see appendix D) gave very similar results to the one described above for the TOT-series.

2. Adjustment for random changes

Smoothing the series for random changes can be done by applying a symmetric moving average of 1 to 6 months (see KB (1997) and OECD (1987b)). However, it is also possible to derive the irregular component via the Census X-11 procedure.

An overview of all observed series together with the corresponding trend-cycle component (i.e. the original series adjusted for seasonal and irregular factors) is visualised in figure E2 (see appendix E). Additional insights can be gained if we present some results in the frequency domain[10]. With spectral analysis the variance of a time series can be broken down into a number of components, the totality of the components being called the spectrum. Each component is associated with a particular frequency and represents the contribution that frequency makes to the total variability of the series (Percival and Walden (1993)). Panel 1 in figure C1 (see appendix C) visualises the

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[9] Note that we also tested whether the series had to be corrected for trading-day effects. A high value for the F-statistic indicated a lot of trading-day variation in the data, hence this correction was necessary (results not shown here).

[10] Unemployment will now be used as the example because spectral analysis requires a large number of observations.

spectral density function[11] of the original unemployment series (UNEMPL) expressed in function of the frequency (ranging from 0 to π) and the period (time from 0 to 216). The first presentation indicates that the density is very large for low frequencies and small for high frequencies. Hence, a high proportion of the variability appears to be connected with cycles of rather long length. The second presentation, representing the periodicity of the series, shows that cycles of 1 month get a very low weight (intensity), while the cycles of 80 to 180 months are dominating. Adjusting this series for seasonal and irregular components via the Census X-11 technique resulted in the series UNEMPLTC. Panel 2 of figure C1 depicts its spectral density function. Compared to panel 1, we notice that the adjustment procedure did not alter the amplitude (intensity), but it removed some smaller peaks at higher frequencies (and lower periodicities).

3. Trend estimation

The issue of detrending is typically related to the issue of what business cycles are, because business cycles are defined as deviations from the trend of a time series. Hence, the trend estimation method determines which part of the series is described as trend behaviour and which part can be conceived as the cycle. Selecting the appropriate detrending method is however very difficult, because of two reasons. At first, researchers disagree about the properties of a trend (deterministic or stochastic) and about the relationship between the trend and the cyclical component (correlated or uncorrelated)[12]. Secondly, their is a debate about whether one has to use a statistically-based or an economic-based detrending method[13].

Table B1 (see appendix B) gives an overview of 11 detrending techniques[14]. As is obvious from this table, different detrending methods embed different assumptions about the trend and the cyclical component. Mainly because of the limited number of observations available and the possibility to extract a stochastic trend, we opted for the Hodrick-Prescott method (HP). This method, developed by Hodrick and Prescott (1980),

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[11] Parzen weights were used to smooth the periodogram and produce an estimate of the spectral density of the series.

[12] According to Canova (1993), neither dynamic economic theory nor the empirical literature gives an indication of the precise relationship between cyclical and trend components.

[13] A statistical method is based on the assumption that the trend and the cycle are unobservable, while an economic method assumes that the choice of the trend is determined by an economic model, by the preferences of the researcher or by the question being asked.

[14] This overview is based on Canova (1993, 1994). A detailed description of the Beveridge-Nelson method and the Unobservable Component model can be found in Doz, Rabault and Sobczak (1995).

is a very popular and widely used detrending technique, especially in the real business cycle literature. This procedure has both an economic and a statistical justification. At first, the HP-filter is a very flexible tool because the researcher can extract a trend according to his preferences and research purpose (e.g. analysing long-term cycles of 10 to 15 year or shorter cycles of only 2 to 4 years). From a statistical viewpoint, the HP-filter is a good extractor of a trend which is stochastic but moves smoothly over time[15] and is uncorrelated with the cyclical component (Canova (1993)).

Suppose we observe the values X_1 through X_S and want to decompose the series into a trend (T_s) and a stationary component (X_s-T_s). The HP-filter determines the trend component series $\{T_s\}$by minimizing the following sum of squares:

$$(1/S)\sum_{s=1}^{S}\left(X_s - T_s\right)^2 + (\lambda/S)\sum_{s=2}^{S-1}\left[\left(T_{s+1} - T_s\right) - \left(T_s - T_{s-1}\right)\right]^2$$

The parameter λ is an arbitrary constant ($\lambda > 0$), reflecting the penality for fluctuations in the trend series. The larger the value of λ, the larger this penality; hence the smoother the path of the estimated trend. In the extreme case, as $\lambda \to \infty$, the trend approaches a linear time trend. If $\lambda = 0$, the sum of squares is minimized when $X_s=T_s$; hence the trend is equal to the original series X_s. Note that the "optimal" value of λ depends on the time series and can be derived by means of a "signal extraction-prediction error decomposition"[16]. The ratio of the variances of the cycle and the trend obtained by this method corresponds to the parameter λ $\left(\lambda = \sigma_C{}^2/\sigma_T{}^2 \quad or \quad \lambda^{1/2} = \sigma_C/\sigma_T\right)$. Most empirical work, however, simply assumes a particular value for λ, equal for all the series under investigation. Applications with quarterly data usually set λ=1600, which corresponds to the 'prior view' of Hodrick and Prescott (1980) that the cyclical component may change by 5%, while the trend component is allowed to vary by 1/8 of 1% in a quarter. Hence the standard deviation of the cyclical component is assumed to be forty times the standard deviation of the trend component, which results in a filter which extracts cycles of average amplitude of 4 to 6 years. Table B2 (appendix B) presents an overview of the most important advantages and disadvantages of the Hodrick-Prescott technique and compares it with four alternative methods widely used for detrending data. Note that it is very difficult to indicate the most appropriate technique. Different detrending methods

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[15] Smoothness is imposed by assuming that the sum of squares of the second differences of T_s (see second term in the formula) is small (Canova (1994)).

[16] More information on this technique can be found in den Butter, Coenen and van de Gevel (1985).

emphasize cycles of different length in the data and have therefore different implications for the timing of turning points[17]. Furthermore, the second order properties (standard deviations and cross correlations of the cyclical components) may vary greatly across detrending methods, even among methods which extract cycles of comparable length. But, as shown by Canova (1993), the higher moments (skewness and excess kurtosis) are more robust to the choice of detrending.

In our application, detrending was done via the Hodrick-Prescott method mainly because the rather short sample periods required a technique which can be applied on all the observations of the series. The smoothing parameter λ was set equal to the benchmark value of 14400, which is the recommended value for monthly data by Hodrick and Prescott. As is obvious from figure E3 (see appendix E), this results in a nonlinear trend (TOTT) which moves smoothly over time. In order to test the sensitivity of our results with respect to the value of the smoothing parameter, we have been experimenting with alternative values for λ . As you notice from figure E3, setting λ =1000000 results in an approximation to a linear trend, while λ =100 leads to a very flexible trend because the penalty for fluctuations in the trend is relatively low in this last case. In order to clarify the effect of different values for λ, we will now make a small digression to the frequency domain. The Hodrick-Prescott filter is called a low-pass filter because it 'passes on' the low frequency signals and suppresses all components with high frequencies. This feature becomes very clear if we plot the gain or frequency response function[18] of the HP-trend and cyclical filter[19], respectively presented in figure 3 and 4.

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[17] Canova (1994) examined the sensitivity of turning points classification to the 11 detrending methods (see table B1) and the ability of each method to replicate NBER dating of business cycles. They concluded that the HP and FREQ filters appear to be the most reliable tools to reproduce standard NBER classifications.

[18] In case of symmetric filters (such as the HP-filter) the gain function equals the frequency response function, because symmetric filters do not induce a phase shift.

[19] As shown by King and Rebelo (1993), the Fourier transform or the frequency response function of the HP cyclical filter can be written as:

$$\tilde{C}(\omega) = \frac{4\lambda\,[1-\cos(\omega)]^2}{1+4\lambda\,[1-\cos(\omega)]^2}$$ where λ is the smoothing parameter and ω is the frequency in radians.

One can easily show that $\tilde{C}(0) = 0$ and $\tilde{C}(\pi) = [16\lambda/(1+16\lambda)] \approx 1$

Figure 3: Gain function of the HP-trend filter

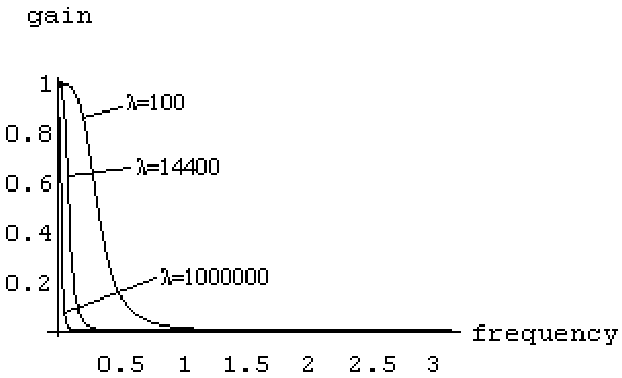
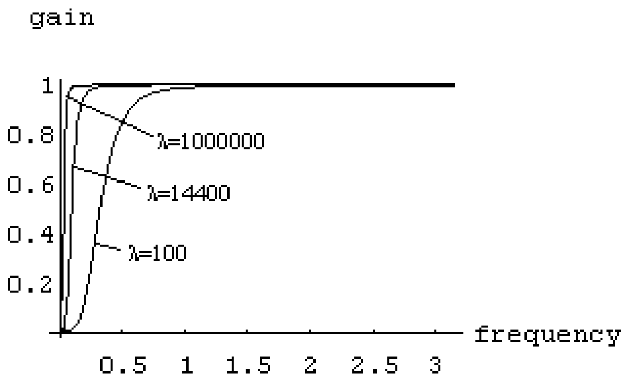


Figure 4: Gain function of the HP-cyclical filter



The top graph shows that the HP-trend-filter places unit gain at zero frequency and zero weight on the high frequencies. Furthermore, it is obvious that the filter removes substantial low frequency variation. Figure 4 indicates that the HP-cyclical filter places zero weight on the zero frequency and close to unit weight on high frequencies. Note that lower values of λ (more flexible trend) shift the gain function to the right. This implies that less frequencies in the lower end of the spectrum will be completely suppressed (zero weight) via the trend filter, hence more low frequency variation will be filtered via the cyclical filter.

Now that we know how different frequency components are filtered via the HP-method, we can compare the spectral density function (SDF) of the unemployment series before (see UNEMPLTC: panel 2 in fig.C1) and after detrending (see UNEMPLC: panel 3 in fig.C1) via HP (with λ=14400). A comparison of the SDF plotted against the frequency mainly shows a large drop in the magnitude (intensity) of the lower frequency components. The effect of the HP-detrending procedure is however more obvious if we look at the plots presenting the periodicity of the series. Besides the drop in the amplitude, the graph of UNEMPLC also indicates that a higher proportion of the variability is connected with cycles of shorter length (80 to 100 months). This is not surprising if we remember that the gain function of the HP-cyclical filter places zero weight on the zero frequency and focuses on filtering (i.e. weight between 0 and 1) the frequencies at the lower end of the spectrum. Panel 4 and 5 visualise the SDF of the series detrended via HP with λ respectively equal to 1000000 and 100. Comparing with panel 3, it is obvious that the value of the smoothing parameter has a very significant effect on the intensity (amplitude) of the spectral density functions. As shown by the gain function, larger values of λ (approaching a linear trend), imply less filtering of the lower frequencies, hence these frequencies will show more variability (larger amplitude). Note furthermore that higher (lower) values of λ result in a detrended series with a higher proportion of the variability connected to cycles of longer (shorter) length.

These spectral density functions as well as figure E3 show how different values of λ can affect the estimated trend. It is however important to mention that (as will be shown below) alternative values of λ do not affect the timing of the turning points. Hence, applying the HP-filter with the same benchmark value (λ =14400) to all series is justified given our research purposes of building a composite leading indicator.

4. Deviation cycles

The above described analysis yields estimates for the seasonal, irregular and trend component of each series. Hence, we are now able to derive the cyclical components.

Note that we assumed a multiplicative relationship between the trend and the cycle for all variables. The cyclical component can then be calculated by dividing the trend-cycle component by the estimated trend and multiplying this result by 100.

Figure 5: Cyclical components of TOT for different values of λ

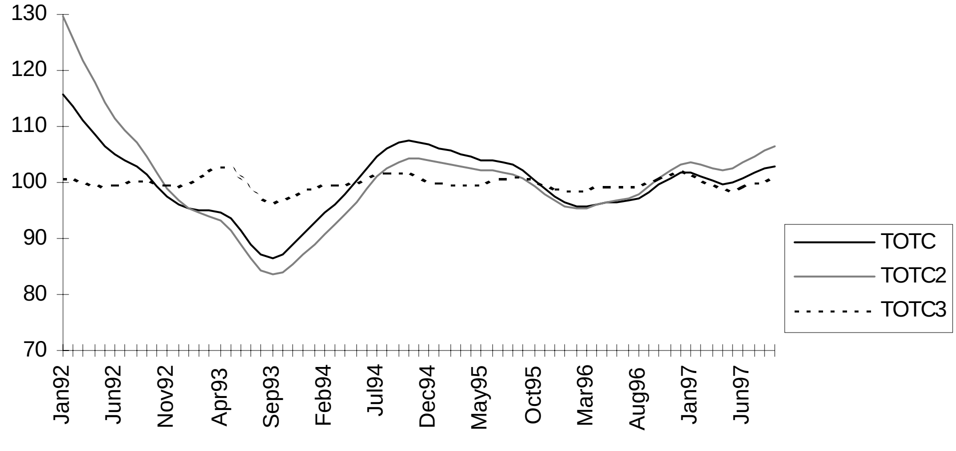


Figure 5 above presents the cyclical component of the TOT-series, labelled as TOTC, derived after HP-detrending at the benchmark value for λ (λ =14400). In addition, this graph depicts the cyclical components derived for alternative values of λ, i.e. TOTC2 is based on TOTT2 (λ=1000000) and TOTC3 on TOTT3 (λ=100).

Note that the larger the value for λ, the smoother the estimated trend, hence the larger the cyclical fluctuations[20]. This should however not cause any problems in our application because all series will be detrended with the same value for λ and all variances will be normalised in one of the following steps. Furthermore, the timing of the turning points, which is crucial when we aim to build a composite leading indicator, is not affected by the choice of λ. Hence, we will continue only with the series detrended on the basis of the benchmark value for the smoothing parameter (λ=14400). Figure E4 (see appendix E) presents for each variable the cyclical component derived on this basis.

2.3. Composite indicator for predicting employment

Combining the cyclical components of several individual series to a composite indicator requires a number of steps.

At first, the different series have to be normalised so that the cyclical patterns have the same mean and standard deviation[21]. Otherwise, it is possible that indicators with strong cyclical fluctuations would dominate the cyclical pattern of the composite indicator.

Normalisation[22] is done according to the following formula: $\left(\left(C-\mu_C\right)/\sigma_C\right)+100$

where C is the cyclical component and μ_C and σ_C respectively its mean and its standard deviation. As a result, all cyclical series have mean 100 and unit standard deviation.

The second step consists of synchronising the different indicators. This is important in order to ensure that, on average, the turning points coincide and to ensure the reconstruction of the “appropriate” time-pattern of the business cycle. Usually, turning points of the cyclical component of the reference series determine the dating of the turning points of the business cycle. Therefore, leading series are lagged, while lagging

[20] The standard deviations are respectively equal to 6.033 (for TOTC), 8.783 (for TOTC2) and 1.265 (for TOTC3). Note however that the higher moments are quite robust to the value of λ, i.e. the skewness varies between -0.062 and 0.786 and the kurtosis between 3.010 and 4.796.

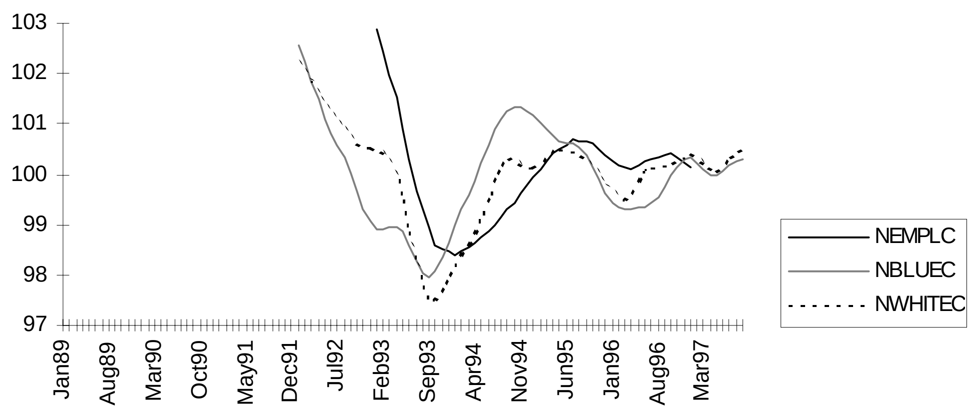
[21] Normalising means is not necessary if the cycles are expressed as deviations from the mean. Furthermore, one should not normalize the amplitudes if these differences are taken into account when determining weights for the composite indicator.

[22] Normalised series have an “N” in front of their name (e.g. NTOTC).

series will be brought forward[23]. The leading character of a series is not only determined on the basis of this turning point analysis, but also by maximizing the correlation between the indicators and the reference series. In our application, it is quite difficult to synchronise the different cyclical indicators, because we lack a good reference series for the labour market due to the nonexistence of monthly employment series in Belgium. In order to get some idea of the cyclical pattern of total employment, the quarterly data on the normalised cyclical component of the EMPL-series (referred to as NEMPLC) has been converted -via linear interpolation- to monthly frequency. All normalised cyclical indicators are then changed in time (lagged or leaded) in order to maximise the correlation with NEMPLC and synchronise the turning points. Table D2 (see appendix D) gives an overview of these correlation coefficients.

We now come to the final step in the analysis, namely the aggregation of several (normalised and synchronised) cyclical components into a composite leading indicator. Before doing so, we want to find out whether interim employment on its own is a good indicator of the future evolution of total employment. Figure 6 below visuales the cyclical pattern of the total number of hours worked during 1 month by white and blue-collar interim workers (NWHITEC and NBLUEC) and the reference series (NEMPLC).

Figure 6: The normalised cyclical component of BLUE, WHITE and EMPL.



From this, it is very clear that interim employment is leading the actual employment series. Note that NWHITEC and NBLUEC are leading NEMPLC with respectively 2 and 9 months[24]. Given the publication lag of 12 months for the employment series, interim employment can predict 14 to 21 months ahead. Another main advantage of

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[23] Usually only leading series are used for constructing a composite indicator.

[24] At these lags the correlation with the reference series is maximised (see table D2) and the turning points are synchronised.

using NBLUEC or NWHITEC as a predictor of NEMPLC is that data on only 1 variable has to be collected. But it is also important to test the predictive performance of these two series and to analyse whether the addition of other variables can lead to more accurate predictions of total employment. The evaluation of the accuracy of forecasting will be based on four test statistics (namely the mean absolute error (MAE), the mean-squared error (MSE), the root mean-squared error (RMSE) and the Theil U-statistic (U))[25], regression analysis[26] and plots of the actual versus the fitted values. As shown in table 2 below, these test statistics do not differ significantly between both interim series. But in contrast, two other evaluation criteria show a better performance of NWHITEC(-2), compared to NBLUEC(-9). On the one hand, the β-coefficient from the regression results is much closer to 1, while panel 1 and 2 in figure E5 (see appendix E) indicate that NWHITEC(-2) does much better in predicting the exact timing of the turning points.

Table 2: Results measuring the accuracy of forecasting NEMPLC[27]

	Test statistics				Regression results		
	MAE	MSE	RMSE	U	α	β	$\bar{R}^2$
NBLUEC(-9)	0.547	0.406	0.637	0.0064	21.468 (1.381)	0.786* (5.037)	0.641
NWHITEC(-2)	0.483	0.440	0.663	0.0066	10.280 (0.752)	0.900* (6.517)	0.669
EMPLINDIC1	**0.341**	**0.296**	**0.544**	**0.0054**	**-7.630** **(-0.508)**	**1.079*** **(7.112)**	**0.757**
EMPLINDIC2	0.301	0.250	0.450	0.0050	-4.010 (-0.278)	1.043* (7.183)	0.802

25 These test statistics are defined as follows: $$U = \sqrt{\frac{\frac{1}{n}\sum_i (y_i - \hat{y}_i)^2}{\frac{1}{n}\sum_i y_i^2}}$$

$$MAE = \tfrac{1}{n}\sum_i |y_i - \hat{y}_i| \qquad MSE = \tfrac{1}{n}\sum_i (y_i - \hat{y}_i)^2 \qquad RMSE = \sqrt{\tfrac{1}{n}\sum_i (y_i - \hat{y}_i)^2}$$

where y, $\hat{y}$ and n are respectively the actual value, the predicted or forecast value and the number of observations.

26 Because all variables have been detrended, we regress the actual value (here NEMPLC) on the predicted values, hence $y = \alpha + \beta\,\hat{y}$. A predictor is good if the estimate of β does not differ significantly from 1. Values of α significantly different from 0 indicate a (positive or negative) bias in the prediction.

27 The t-ratios are based on the Newey-West heteroskedasticity and autocorrelation consistent standard errors and the coefficient estimates for β indicated with * are not significantly different from 1 at 5% significance level.

Because the NWHITEC-series only reflects cyclical movements in the temporary labour market (for white-collar jobs), we will now add a variable which is explicitly related to the destruction of permanent employment, namely the total number of business failures (NFAILC). Hence, we propose the following composite indicator for predicting total employment in Belgium[28]:

EMPLINDIC1= [NWHITEC(-2)+ iNFAILC(-10)] / 2

As can be seen from table 2, this composite indicator gives more accurate forecasts of NEMPLC. Furthermore, figure E5 illustrates that the addition of this variable reduces the forecasting errors and improves significantly the prediction of the turning points in the reference series. Hence, the benefits of this composite indicator exceed the associated costs of collecting data on one more series and aggregating two variables which are quite highly correlated with eachother[29].

Note that the aggregation in the above described employment indicator is done by giving equal weights to the different components. Alternatively, one can use an unequal-weighted system, where the weights can for example be determined via correlation or principal component[30] analysis. We have been experimenting with the latter technique on the two series used in the above specified employment indicator, namely NWHITEC and iNFAILC (results not shown here). But because the coefficients for the first principal component[31] showed that both series are about equally weighted, there is no purpose to use an unequal-weighted system[32].

In order to make the link between the product and labour market more explicit, we will now add a product market variable, namely NSALESC (at its optimal lag with the

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[28] Because business failures are inversely related to employment, we take the inverse of the normalised cyclical component of the FAIL-series (called "iNFAILC") when constructing a leading indicator for employment.

[29] The correlation coefficient between NWHITEC(-2) and iNFAILC(-10) equals 0.779.

[30] Principal component analysis (see Jolliffe (1986) and Berk and Bikker (1995)) summarizes high dimensional data into a few dimensions. Each dimension is called a principal component and represents a linear combination of the variables. Principal components can be computed from the correlation or the covariance matrix. The first principal component is the linear combination of the variables that accounts for the greatest possible variance. In our application, this component can be interpreted as the business cycle. In order to get appropriate weights for a composite indicator, the coefficients of the first principal component have to be divided by the standard deviations of the associated series and rescaled to ensure that the sum of the weights equals 1. Hence, the weight derived for each individual series will be proportional to the correlation with the business cycle (as defined by the first principal component) and inversely correlated to its amplitude.

[31] Note that the first principal component accounted for approximately 90% of the total variance.

[32] In addition, we used OLS-regression coefficients as weights. This resulted in an alternative leading indicator which performed not significantly better than EMPLINDIC1.

reference series), to the above described employment indicator. This results in the following alternative specification:

EMPLINDIC2=[NWHITEC(-2)+iNFAILC(-10)+NSALESC(-9)] / 3

Table 2 above indicates that this specification leads to more accurate forecasts of total employment, but note that these results are not significantly different from EMPLINDIC1. Furthermore, panel 4 in figure E5 (see appendix E) shows that EMPLINDIC2 does worse in predicting the timing of the turning points in the reference series. Hence, the addition of the product market variable does not lead to a better leading indicator for total employment. This seems to suggest that either spillovers from the product to the labour market are insignificant or -more plausibly- that our selected labour market variables (i.e. interim employment and business failures) are sufficiently able to capture these spillovers.

From the above described analysis we can conclude that although interim employment gives a clear indication of the cycles in the reference series, more accurate forecasts of the future levels of, as well as the turning points in, total Belgian employment can be derived by a composite indicator (EMPLINDIC1) constructed on the basis of white-collar interim work and the number of business failures.

A final test for our constructed employment indicator is to compare its performance with the performance of the existing leading indicators. Before proceeding with this comparison, we need to introduce four new variables. KBINDIC is the leading indicator for the product market developed by the Kredietbank[33]. INDIC1 and INDIC2 are two synthetic indicators of the National Bank of Belgium (NBB), related respectively to the total economy and the manufacturing sector only. From the monthly firm survey of the NBB it is also possible to get data on the expected employment evolution in the manufacturing sector for the following 3-months period (PREDEMPL). All four series are then normalised as explained before and this results in the series NKBINDIC, NINDIC1, NINDIC2 and NPREDEMPL.

Table 3 below presents the test statistics and regression results measuring the accuracy of forecasting NEMPLC via these existing leading indicators.

[33] An elaborate description of the KB-indicator can be found in KB (1997).

Table 3: Results measuring the accuracy of forecasting NEMPLC by existing indicators

	Test statistics				Regression results		
	MAE	MSE	RMSE	U	α	β	$\bar{R}^2$
NKBINDIC(-6)	0.860	1.166	1.080	0.0108	-53.404 (-1.908)	1.547* (5.461)	0.637
NINDIC1(-10)	0.690	1.055	1.027	0.0103	30.725 (1.915)	0.670* (4.325)	0.340
NINDIC2(-10)	0.772	1.112	1.055	0.0106	46.283 (3.342)	0.540 (3.904)	0.295
NPREDEMPL(-8)	0.680	1.163	1.078	0.0108	36.369 (2.113)	0.640 (3.726)	0.280

From a comparison of table 2 and 3, it is very clear that all existing leading indicators give significant less accurate forecasts of NEMPLC (i.e. higher values for the test statistics, lower values for $\overline{R}^2$ and β-coefficients less close to 1). Furthermore, table D2 (appendix D) indicates lower correlation coefficients between these indicators and the reference series, compared to our constructed employment indicator. And finally, plots of the actual versus the fitted values (see panel 5 and 6 in figure E5) show that these existing leading indicators are not able to give precise predictions of the turning points in NEMPLC. Hence, this proves the value-added of our leading indicator (EMPLINDIC1) designed especially to predict the cyclical pattern in the labour market.

2.4. Extension: adding an AR(2)-process for employment to the constructed employment indicator

In this section we will first present an autoregressive process for employment in order to find out how well information on the past behaviour of employment helps to predict future values of this series. Afterwards we will add our constructed employment indicator (EMPLINDIC1) to this AR-process for the reference series and test whether our indicator has any value-added with respect to predicting the cyclical pattern of total employment. An autoregressive process for the (normalised) cyclical component of employment can be written as:

$$y_t = C + \gamma\, y_{t-i} + \delta\, y_{t-(1+i)} \qquad (1)$$

where y equals NEMPLC. Note that we opted for an AR(2)-process because -for our research purposes- information on turning points is very important. Furthermore, in order to make the analysis realistic, we should choose i equal to the publication lag of the reference series. As mentioned before, the R.S.Z. publishes figures on total employment in Belgium with 12 months delay, hence i=12 in our application.

Estimating equation (1) for the period 93:01-97:01 results in the following estimates for the adjustment speed coefficients: $\hat{\gamma} = 2.173$ and $\hat{\delta} = -2.243$. Future values of employment can then be forecasted as follows (y equals NEMPLC):

$$\hat{y}_t = \hat{C} + \hat{\gamma}\, y_{t-i} + \hat{\delta}\, y_{t-(1+i)} \quad (2)$$

Let us name this series EMPLAR and compare its predictive performance with EMPLINDIC1. Table D2 (see appendix D) shows that EMPLAR has a slightly higher correlation coefficient with NEMPLC and from table 4 below (compared to table 2), we can notice that the test statistics as well as the regression results indicate more accurate forecasts. Panel 7 in figure E5, however, visualises that EMPLAR is not able to predict the timing of the turning points very well. This is not surprising because EMPLAR is only based on information from the past behaviour of employment and cycles are not always of the same length.

Table 4: Results measuring the accuracy of forecasting NEMPLC

	Test statistics				Regression results		
	MAE	MSE	RMSE	U	α	β	$\bar{R}^2$
EMPLAR	0.229	0.073	0.270	0.0027	2.40E-05 (2.46E-06)	1.000* (10.244)	0.827
EMPLINDIC3	0.161	0.035	0.187	0.0019	-3.044 (-0.591)	1.031* (19.926)	0.921

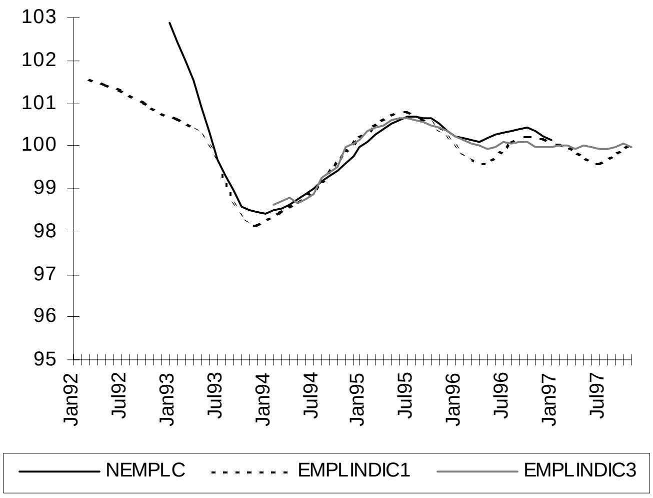
We will now test whether these results can be improved by adding our constructed employment indicator (EMPLINDIC1) to EMPLAR. Aggregation with equal weights[34] gives the following specification:

EMPLINDIC3= [EMPLAR+ EMPLINDIC1] / 2

This specification does not only increase the correlation with NEMPLC (0.961, see table D2), but it also leads to a further reduction in the forecasting errors (see table 4). And even more importantly, the addition of EMPLINDIC1 results in much better predictions of the exact timing of the turning points (see panel 8 in figure E5). Figure 7 illustrates how the employment indicator (EMPLINDIC1), constructed on the basis of NWHITEC(-2) and iNFAILC(-10), can be improved by adding an AR(2)-process (resulting in EMPLINDIC3) in order to predict the reference series (NEMPLC).

[34] Calculating weights via principal component analysis or an OLS-regression (results not shown here) did not alter the outcome because in both cases EMPLAR and EMPLINDIC1 were assigned (approximately) equal weights.

Figure 7: Comparison between EMPLINDIC1 and EMPLINDIC3 in predicting NEMPLC



As a conclusion we can say that information on the past behaviour of total employment (captured by the AR(2)-process) seems to be very useful in predicting the general cyclical pattern of the reference series, while current data on interim employment and business failures (combined in EMPLINDIC1) has a value-added because it gives more accurate information on the timing of the turning points and the exact length of the cycles. Note however that because official data on total Belgian employment is published with a delay of 12 months, the AR(2)-process specified above can not play a role as a leading indicator, while EMPLINDIC1 can predict the reference series up to 14 months ahead. Our constructed leading indicator thus has a value-added for labour market analysts and policy-makers.

2.5. Composite indicator for predicting unemployment

Although the main aim of this paper was to construct a leading indicator for total employment in Belgium, this section will shortly deal with unemployment as the reference series. As mentioned on p.2, unemployment is a better reference series because monthly data can be collected for a much longer period (1980:01-1997:12). But there is less need to construct a leading indicator for predicting future values of this series because Belgian unemployment figures are published with maximum 1 month of delay. As will be shown below, an AR(2)-process for unemployment with a lagstructure corresponding to the actual publication delay of only 1 month will outperform any indicator constructed on the basis of some labour market variables.

Estimating equation (1) for the normalised cyclical component of unemployment (NUNEMPLC) over the period 1980:01-1997:12 (with i=1) gives the following results: $\hat{\gamma} = 1.861$ and $\hat{\delta} = -0.895$. Forecasts of unemployment (called UNEMPLAR) can be derived as indicated in equation (2).

Table 5: Correlation coefficients and regression results forecasting NUNEMPLC[35]

	Correlation coefficient with NUNEMPLC	Regression results α	β	$\bar{R}^2$
UNEMPLINDIC1 (=iEMPLINDIC1)	0.858	1.499 (0.151)	0.987* (9.968)	0.732
UNEMPLAR	0.998	-0.380 (-0.414)	1.004* (110.203)	0.996
UNEMPLINDIC2	0.966	-7.320 (1.596)	1.074* (23.442)	0.932

Table 5 compares the forecasting performance of UNEMPLAR and the inverse of our previously constructed leading indicator (EMPLINDIC1)[36]. As expected, the former series has significantly smaller forecasting errors and a higher correlation with the reference series.

35 All results refer to the same sample period (1992:03-1997:11).

36 Because EMPLINDIC1 is designed to predict total employment and this reference series is inversely related to unemployment, we take the inverse of EMPLINDIC1 (called UNEMPLINDIC1). Note that a slightly different specification could be constructed in order to maximise the correlation and synchronisation between the selected series (i.e. interim employment and business failures) and unemployment (rather than employment). This, however, did not alter the results significantly.

Furthermore, we tested whether the addition of the inverse of EMPLINDIC1 to this AR(2)-process improves the results even more. Aggregation with equal weights leads to the following specification:

UNEMPLINDIC2= [UNEMPLAR+ iEMPLINDIC1] / 2

As is obvious from table 5, this transformation did not improve the performance compared to the simple AR(2)-process. Note however that these results depend crucially on the lagstructure of the AR(2)-process. As in the case of total employment, our constructed leading indicator would have a real value-added for predicting unemployment if data on this reference series would be published with a delay of minimum 4 months.

As a conclusion we can say that the future cyclical pattern of unemployment can nearly perfectly be predicted by information on its past behaviour, captured by an AR(2)-process with 1 and 2 months lag. This is due to the strong persistence pattern in unemployment, which can be exploited because unemployment figures are rapidly available. Nevertheless, data on interim employment and business failures (combined in EMPLINDIC1) can also give a reliable indication of the future levels of, as well as the turning points in, unemployment. Furthermore, EMPLINDIC1 can predict unemployment up to 2 months ahead.

3. Conclusion

This paper focused on the construction of a leading indicator for the Belgian labour market. The aim was to use only labour market variables in order to predict the cyclical pattern as well as the turning points in total employment. All selected series were adjusted for seasonal and irregular components via the Census X-11 procedure. Several tests were performed to check the performance of the adjustment results. Then the Hodrick-Prescott method was used for detrending and afterwards the cyclical component was derived for each series. These cyclical components were then aggregated into a composite leading indicator. Several criteria, such as small errors to forecast the reference series and accurate predictions of the turning points, were used in order to select a specification for the employment indicator. This resulted in a leading indicator constructed on the basis of white-collar interim work and the number of business failures. It was shown that this indicator resembled quite well the cyclical pattern of observed employment in Belgium and given the fact that official employment figures are published with at least 12 months delay, the indicator could predict employment 14 months ahead. Secondly, it was found that our constructed employment indicator did not perform significantly better when product market variables were added to the specification (i.e. the forecasting errors became slightly smaller, but the prediction of turning points got worse). Furthermore, the predictive performance of our employment indicator was unambiguously superior to all existing leading indicators for the product market. Nevertheless, our employment indicator could be improved by incorporating information on the past behaviour of the reference series (captured by an AR(2)-process). The autoregressive process for employment seemed to be very useful in predicting the general cyclical pattern of the reference series, while current data on interim employment and business failures -combined in an employment indicator-supplied more accurate information on the timing of the turning points. Note however that given the serious data problems for the reference series, the AR(2)-specification loses its leading character.

Note that we also experimented with a composite indicator for unemployment. But because unemployment shows a very persistent pattern and official data on this series is published with maximum 1 month of delay, a much better indicator could be constructed on the basis of a simple AR(2)-process with a lagstructure equal to this short publication lag. Nevertheless, data on interim employment and business failures can also give a clear indication of the actual cycles in unemployment.

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Appendix A: The X-11 seasonal adjustment programme

In order to simplify the exposition the following description of the X-11 analysis is limited to a monthly time series with a multiplicative seasonal pattern. The model can be written as:

$$X_t = TC_t * S_t * TD_t * I_t$$

where X_t is the original (observed) series; TC_t, S_t, TD_t and I_t are respectively the unobserved trend-cycle component[37], the seasonal component, the trading-day component and the irregular component.

The X-11 programme[38] is divided into seven parts (A to G). Part A is optional and allows the user to make prior adjustments for trading days. In part B, C and D almost identical iterations are performed to provide estimates of the four unobserved components (TC, S, TD and I). Each iteration allows the procedure to make refined estimates of extreme values in the irregular components.

During the first iteration (in part B)[39], a centered 12-term moving average is applied to the original series to provide a preliminary estimate of the trend-cycle component (TC). By dividing the original series by this trend-cycle, a preliminary estimate of the product of the seasonal and irregular component (SI) is obtained. A set of preliminary seasonal factors (S) is then computed by applying a weighted 5-term moving average to the estimated SI-values seperately for each month. Dividing the SI-series by these seasonal factors provides an estimate of the irregular component (I). A moving standard deviation is calculated from the irregular component and is used to assign a weight to each monthly value for measuring its degree of extremeness. These weights are used to modify extreme values in the SI-component. New seasonal factors (S) are then estimated by applying a moving average to the modified SI-component. A preliminary seasonally adjusted series results from dividing the original series by these new seasonal factors. Applying a weighted moving average to this seasonally adjusted series gives a second estimate of the trend-cycle component (TC). The same process is then used to obtain second estimates of the seasonally adjusted series and improved estimates of the irregular component (I). This irregular component is again modified for extreme values

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[37] As is common under most seasonal adjustment techniques, the trend and the cyclical component are combined into a trend-cycle component (TC).

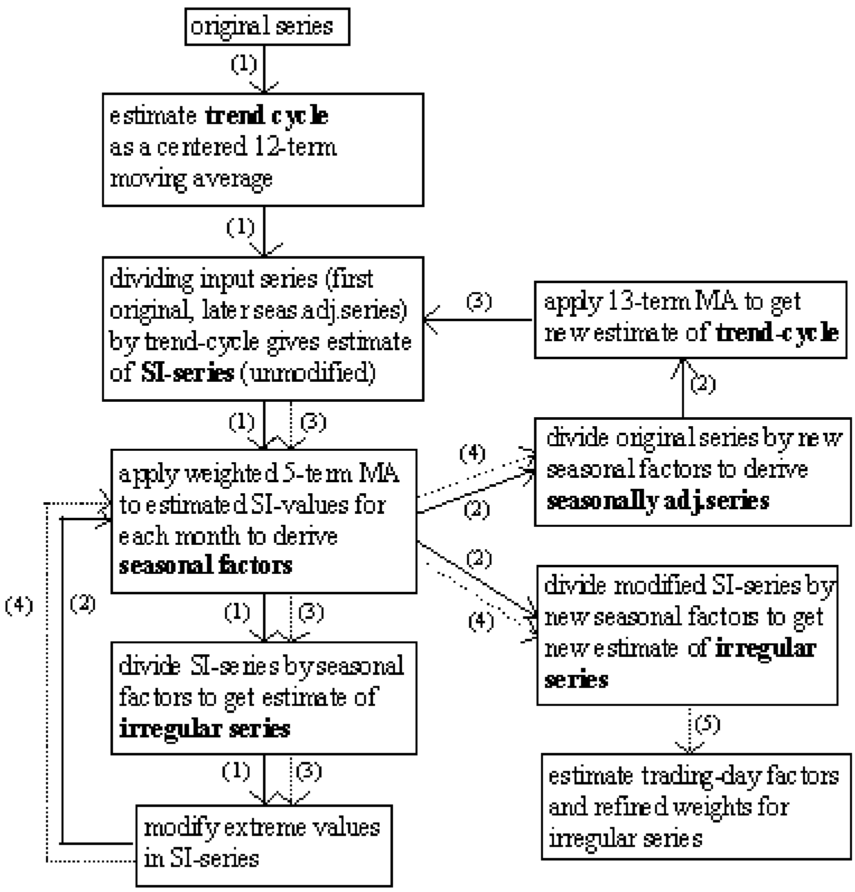
[38] The description of the programme is based on Hylleberg (1992) and the SAS User's Guide.

[39] The different steps of the first iteration are visualised in the flowchart given below.

and used to provide estimates of trading day factors (TD) and refined weights for the identification of extreme values (I).

In part C, a second iteration is performed on the original series adjusted by the trading day factors and irregular weights developed in the first iteration. This iteration consists of the same computations as in part B and gives final estimates of the trading day factors (TD) and irregular weights (I). A third and final iteration (part D) follows the same procedure as in part B and uses the original series adjusted for trading day factors and irregular weights computed during the second iteration. This iteration produces final estimates of seasonal factors (S), the seasonally adjusted series, the trend-cycle (TC) and the irregular components (I). In parts E to G, summary measures, tables and charts are produced to facilitate analyses of the filtering processes made in the parts B, C and D.

Flowchart: X-11 programme - part B



Appendix B: Detrending techniques

Table B1: Overview of 11 detrending techniques

Detrending method	Assumptions on: features of T_t	correl. between T_t and C_t	Method: statist. or econ.
Linear detrending (LT)	T_t is a deterministic process (can be approx. by polynomial functions of time)	uncorrelated	statistical
Segmented detrending (SEGM)	-T_t is a deterministic process (can be approx. by polynomial functions of time) -structural break in T_t at a known time	uncorrelated	statistical
First-order differencing (FOD)	- T_t is a random walk with no drift - C_t is stationary	uncorrelated	statistical
Beveridge and Nelson (BN)	- X_t has a unit root and T_t accounts for its nonstationary behaviour (C_t is stationary) - T_t is the long-run forecast of X_t adjusted for its mean rate of change - decomposition is based on a fitted ARIMA-model for each individual series[a]	perfectly correlated (driven by same shocks)	statistical
Unobservable Components (UC)[b]	- T_t follows a random walk with drift - C_t is a stationary finite order AR process	may be correlated (but can be uncorrelated)	statistical
Frequency Domain (FREQ)[c]	- T_t has most of its power concentrated in a low frequency band of the spectrum - away from zero, the power of the trend component decays very fast - T_t can be deterministic or stochastic (as long as changes are not too frequent)	uncorrelated	statistical
Multivariate Frequency (MFREQ) (one dimensional index)	- in the low frequencies of the spectrum of X_t there exists a one dimensional process T_t which is common to all series - T_t has most of its power concentrated in a low frequency band of the spectrum and away from zero it decays very fast		statistical
Multivariate linear trend (MLT) (Common Deterministic Trend)	- all variables have a common deterministic trend - fluctuations around trend are transitory	uncorrelated	economic
Cointegrating (COIN) (Common Stochastic Trend)	- all variables have a common nonstationary trend - estimate a vector error correction model (VECM) to produce estimates of C_t (incl. cointegration vectors)[d]	perfectly correlated (driven by same shocks)	economic
Blanchard and Quah (BQ)	- T_t has a unit root - C_t is stationary	uncorrelated	economic
Hodrick and Prescott (HP)	- T_t is stochastic, but moves smoothly over time (sum of squares of second differences of T_t must be small) - λ_t regulates the extent of the penalty imposed for large fluctuations in T_t	uncorrelated	statistical + economic

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[a] Note that alternative ARIMA specifications lead to very different decompositions into trend and cycle (Canova (1993)).

[b] Unobservable Components models are usually embedded in a state space framework.

[c] The FREQ- and MFREQ-detrending models require an analysis in the frequency domain instead of the time domain.

[d] As in the Beveridge and Nelson method, estimates of the trend and the cyclical component differ for different specifications of the VECM model (Canova (1993)).

Table B2: Advantages and disadvantages of 5 widely used detrending techniques

Detrending method	Advantages	Disadvantages
Linear detrending (LT)		- failure to remove unit root components
First-order differencing (FOD)	- able to remove unit root components	- filter not symmetric (causes phase-shift)[a] - dramatic re-weighting of frequencies[b] (re-weighting strongly toward higher frequencies, down-weighting lower frequencies)
Moving averages (MA)[c] (two-sided or centered)	- symmetric filter (no phase shift)	- fixed order MA can be problematic if length of cycles changes over time - loss of observations (large number of observations are required)
Phase Average Trend (PAT)[d]	- straight forward and flexible procedure - able to deal with business cycles of varying length - excellent descriptions historical behaviour	- choice of preliminary peak and trough dates - requires large number of observations - method of extrapolation is problematic (estimation at end of sample less reliable) - not suitable for forecasting
Hodrick-Prescott (HP)	- symmetric filter (no phase shift) - removes unit root components[e] - very flexible technique - can be applied to all observations - can extract same trend from set of variables - yields satisfactory results (Berk and Bikker (1995), Canova (1994))	- alters moments of the series (i.e. measures of persistence, variability and comovement) - may create spurious behaviour (Harvey and Jaeger (1993) and Jaeger (1994)) - choice of λ - estimation at end of sample less reliable

[a] This implies that the timing relationship between variables is altered.

[b] If the goal of a business cycle filter is to isolate fluctuations in the data which occur between specific periodicities, without special emphasis on any particular frequency, the first-order differencing filter is a poor choice (Baxter and King (1995)).

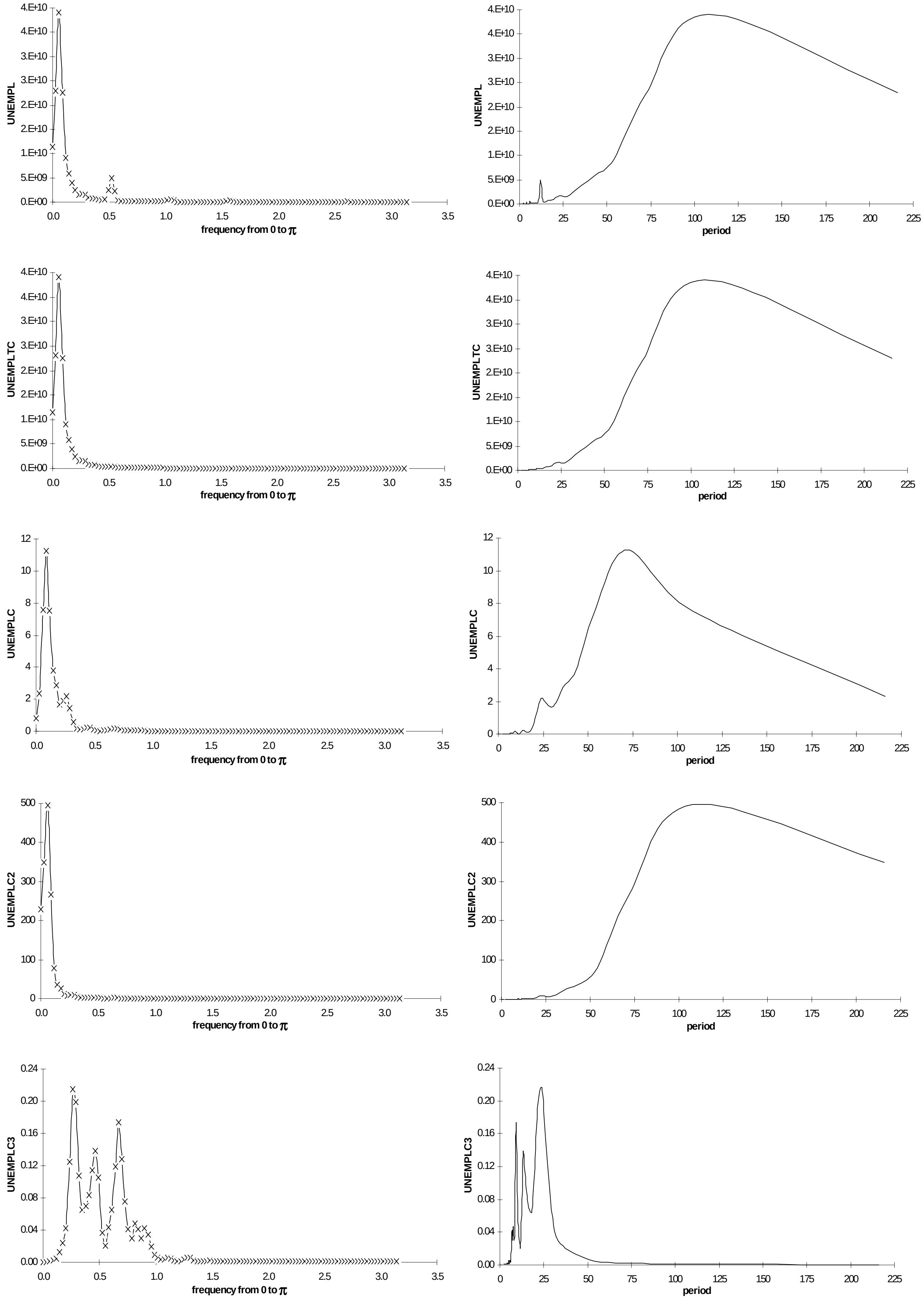
[c] This technique defines and derives the trend component as a two-sided or centered moving average. The order of this symmetric moving average equals the average length of the business cycle, the average being determined by inspection or on theoretical grounds.

[d] The Phase Average Trend method (Boschan and Ebanks (1978), Nilsson (1987), OECD (1987)), developed by the NBER, has been designed especially to separate the long-term trends from medium-term cycles without encountering the problems of the moving average method. The Phase Average Trend of a series is estimated by first splitting the series into phases (i.e. the number of months between successive turning points). The means of the observations in each phase are then calculated and these phase-averages are used to compute a three-term moving average. The values obtained from the moving average are assigned to the mid-point of the three-phase period (a “triplet”) to which they refer. The trend is then obtained by computing the slope between the mid-point of successive triplets and adjusted to match the level of the original data.The trend is extrapolated by constructing a log-linear line extended from the mid-point of the last triplet (Nilsson (1987)). Note that the first step is based on preliminary estimates of the peak and trough dates, hence the turning points, often determined by the “Bry-Boschan” routine (see Nilsson (1987)).

[e] The HP-filter will remove nonstationary components that are integrated of order four or less (King and Rebelo (1993)).

Appendix C: Spectral analysis

Figure C1: Spectral density functions of the unemployment series (in function of frequency and period)



Appendix D: Tables

Table D1: Description of the variables

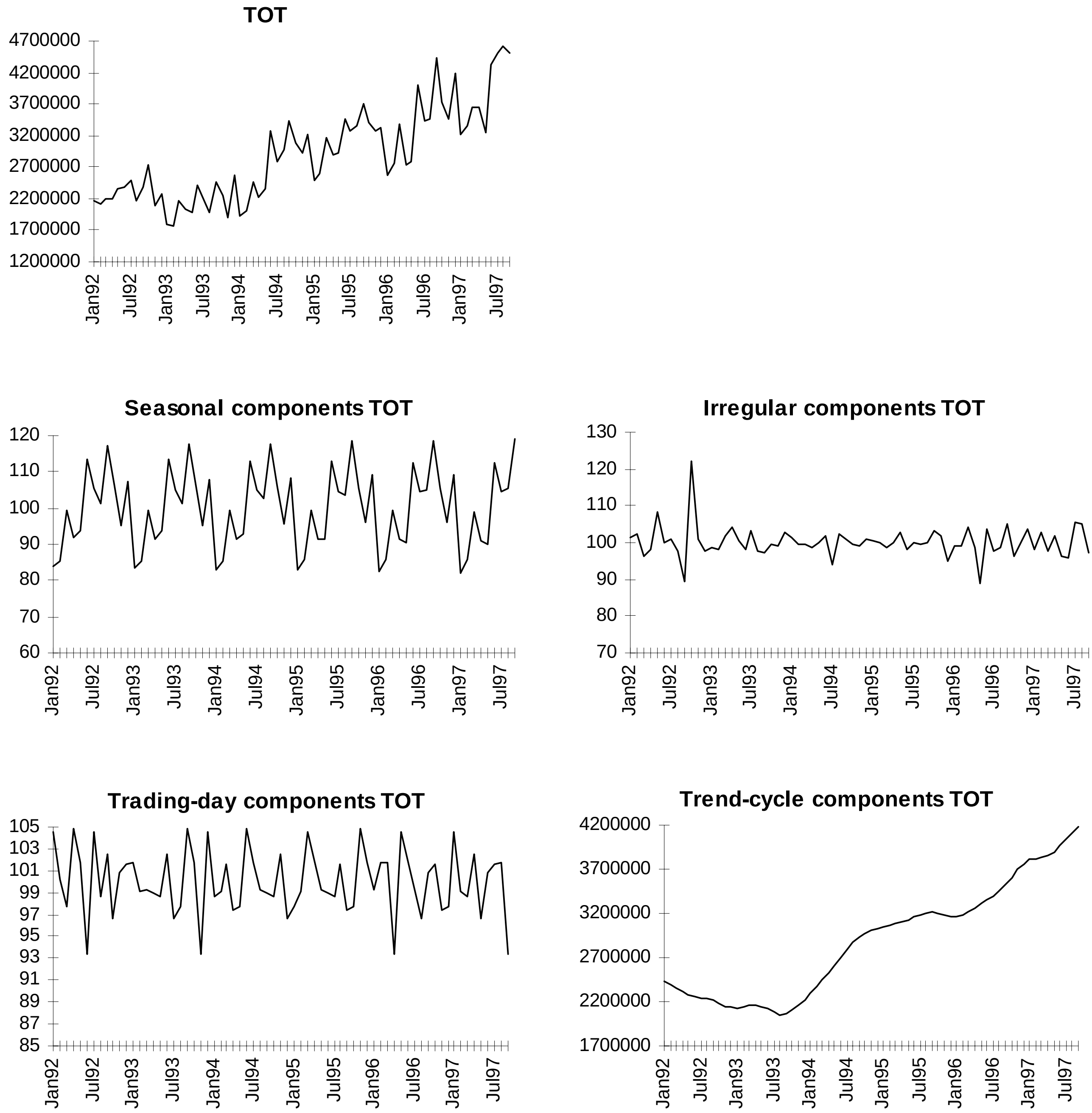
variable	description	source	period
WHITE	total hours worked during 1 month by white-collar interim workers ("bedienden")	UPEDI	92:1-97:9
BLUE	total hours worked during 1 month by blue-collar interim workers ("arbeiders")	UPEDI	92:1-97:9
TOT	total hours worked during 1 month by white and blue-collar interim workers	UPEDI	92:1-97:9
VAC1	cumulated number (over 12 months) of unfilled vacancies (excl.special programmes) at end of the month at the RVA	RVA	89:1-97:6
VAC2	number of vacancies published in the Flemish newspapers during a month	De Standaard	92:1-97:6
FAIL	number of business failures during a month (only companies)	Graydon	89:1-97:9
DISINC	number of disincorporations during a month (only companies)	Graydon	89:1-97:9
START	number of starting businesses during a month (only companies)	Graydon	89:1-97:9
IP	industrial production (indexnumbers)	NIS	89:1-97:5
SALES	sales industrial firms deflated by the indexnumber of industrial production prices	NIS	89:1-97:4
EMPL	number of employees in the private sector *(at end of each quarter)*	R.S.Z.	93Q1-97Q1
UNEMPL	number of unemployed (incl. unemployed older than 50 years)	RVA	80:1-97:12

Table D2: Correlation coefficients between NEMPLC and normalised indicators at the optimal lags or leads.

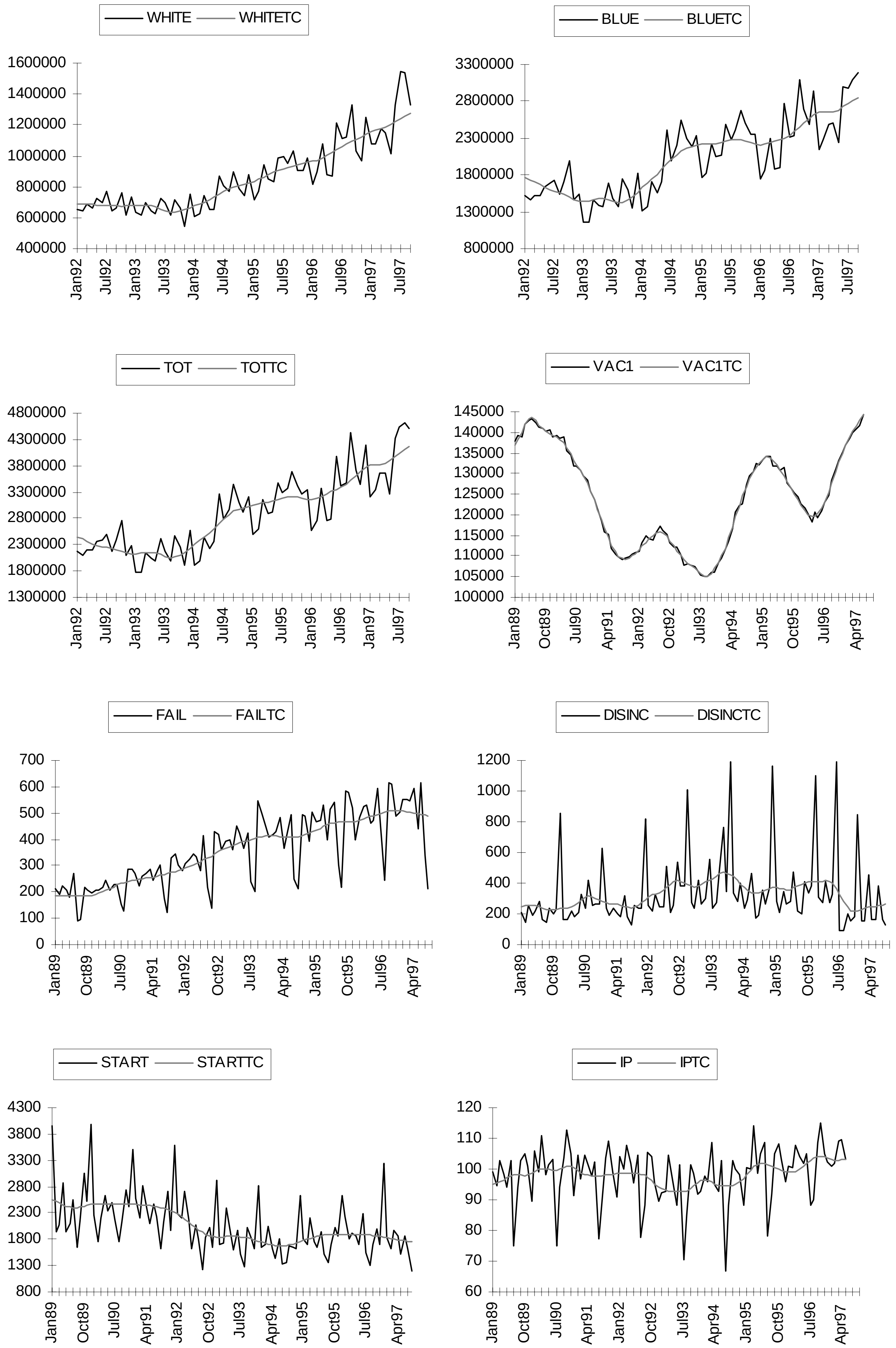
indicator	leads(+) lags(-)	correlat.coeff.		indicator	leads(+) lags(-)	correlat.coeff.
NWHITEC	-2	0.822		NKBINDIC	-6	0.803
NBLUEC	-9	0.805		NINDIC1	-10	0.595
NTOTC	-8	0.763		NINDIC2	-10	0.557
NVAC1C	-6	0.542		NPREDEMPL	-8	0.543
NVAC2C	-3	0.871				
NFAILC	-10	-0.847		**EMPLINDIC1**	0	**0.873**
NDISINCC	+7	0.558		EMPLINDIC2	0	0.898
NSTARTC	+4	0.527		EMPLAR	0	0.912
NUNEMPLC	-3	-0.881		EMPLINDIC3	0	0.961
NIPC	-6	0.539				
NSALESC	-9	0.772				

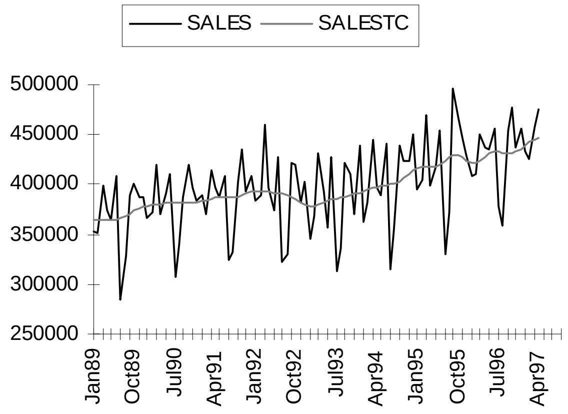
Appendix E: Figures

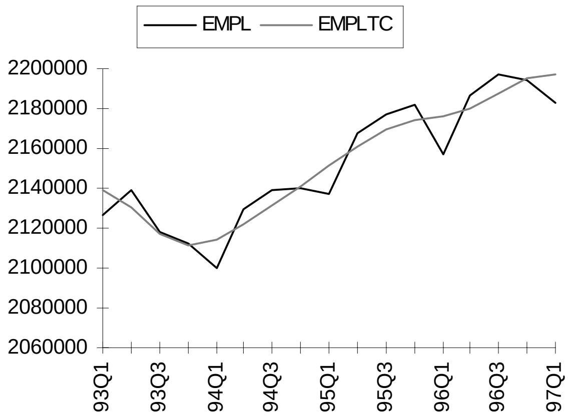
Figure E1: Estimated decomposition of TOT into four components

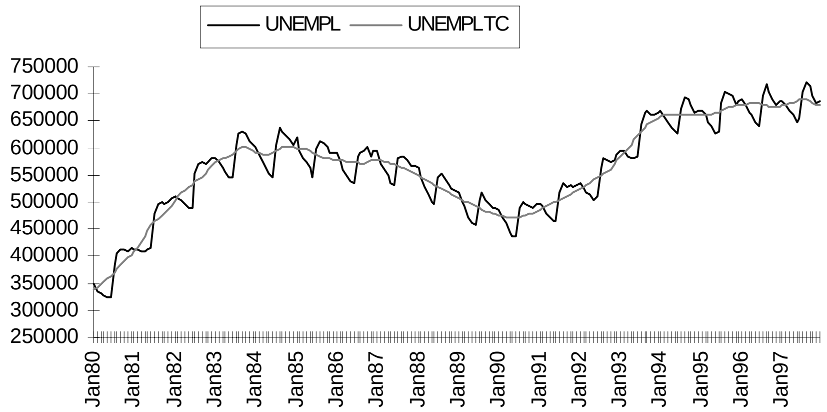


<u>Figure E2</u>: <u>Original series and the series adjusted for seasonal and irregular factors</u>









<u>Figure E3</u>: <u>Estimated trend of TOT for λ=14400 (TOTT), λ=1000000 (TOTT2), λ=100 (TOTT3)</u>

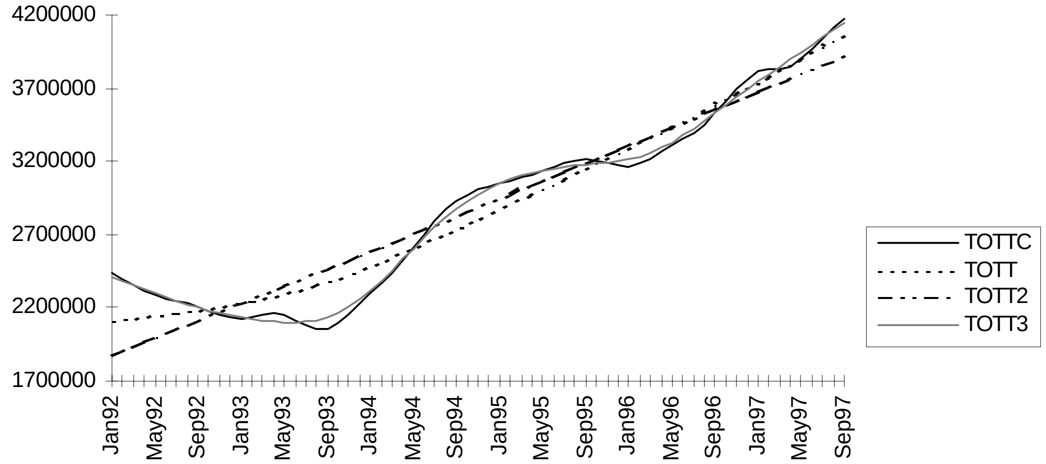


Figure E4: Cyclical components of all series

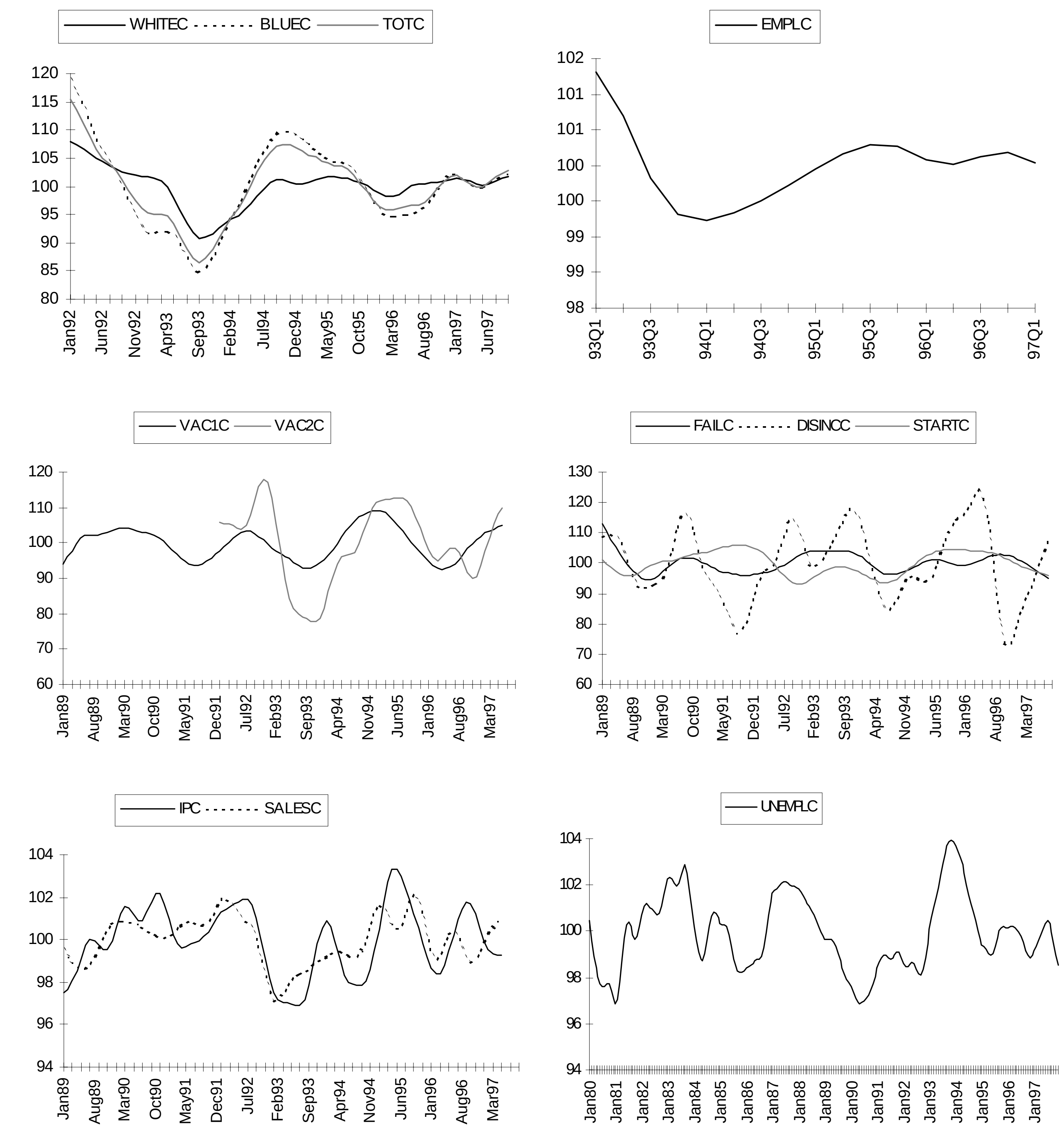
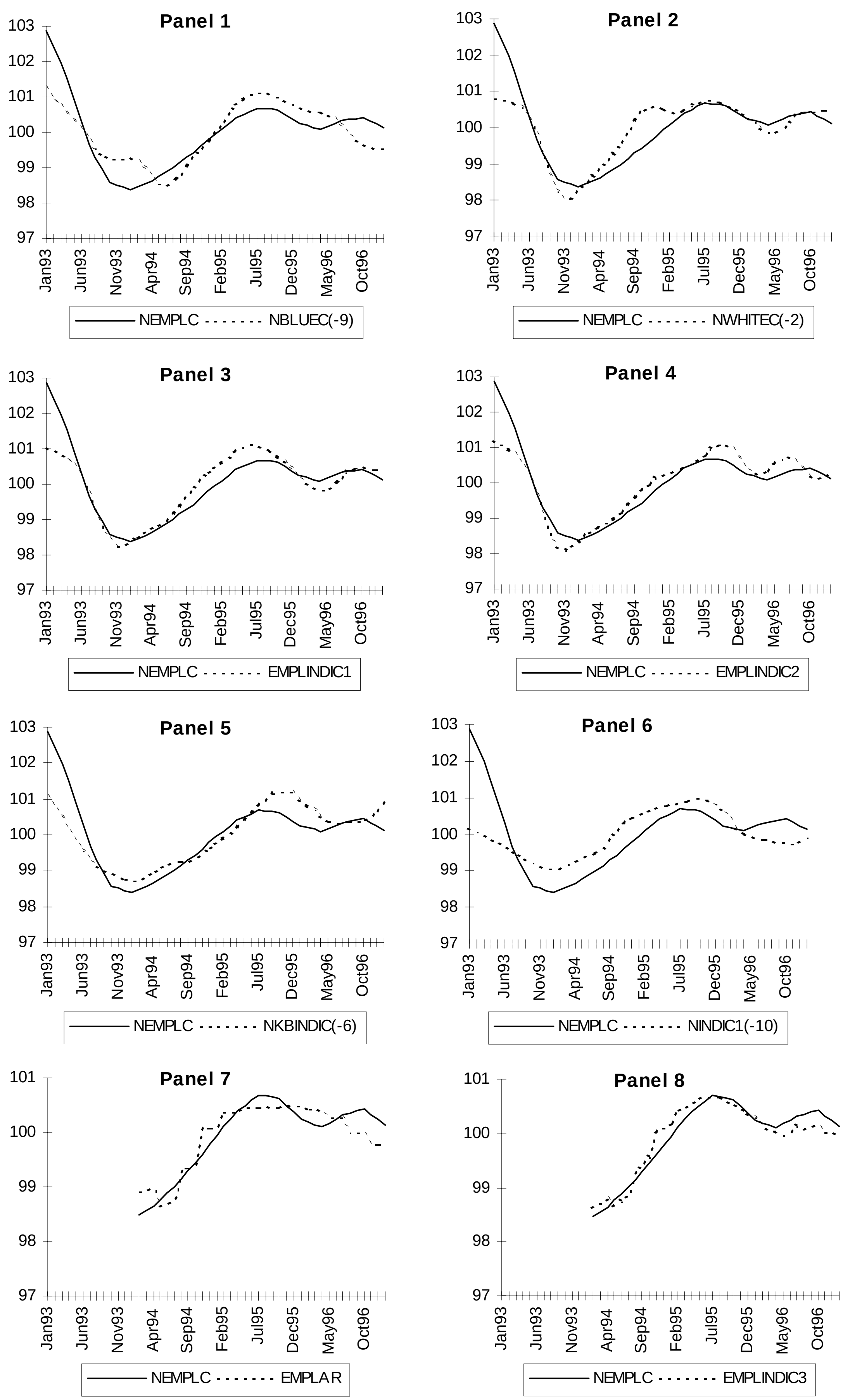


Figure E5: Actual (NEMPLC) versus fitted values of several indicators



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