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THE APPLICABILITY OF THE SECTORAL SHIFT HYPOTHESIS IN THE NETHERLANDS

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The sectoral shift hypothesis in the Netherlands cannot be easily tested for the presence of rigorous structural breaks in the data. Therefore, a Kalman Filter approach is adopted. What we find, is that the variables capturing the sectoral shift hypothesis are the most important in explaining Dutch unemployment behavior during the postwar period. This means that cyclical unemployment in the Netherlands can be viewed as a fluctuation of the natural rate of unemployment.

JEL classification codes: E24, J21

Key words: unemployment, sectoral shift hypothesis

I. Introduction

Generally, it takes time before workers who become unemployed find a new job, certainly when they change jobs between sectors (provided that they find one). This labour reallocation process gives rise to cyclical unemployment. But how is cyclical unemployment embedded in economic theory?

On the one hand, we could say that cyclical unemployment is a deviation

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from a more or less stable natural rate. Alternatively, cyclical unemployment could be defined as a fluctuation of the natural rate itself. The latter perspective was introduced by Lilien (1982), and is called the sectoral shift hypothesis. Over the years, many papers have been issued on mostly American data, showing evidence both in favor and against the hypothesis.[1]

In this paper, we test the sectoral shift hypothesis using Dutch data. We will do so by estimating a Kalman Filter model. This approach has the advantage that we can use time series from 1950 onwards, although there have been rigorous revisions of the data in 1969, 1977 and 1985 (leading to structural breaks in the original series that are difficult to pick up with deterministic methods).[2] The recursive nature of the Kalman Filter assures that shifts in variables over time are signaled as soon as they occur, so that the corresponding shifts in parameter values will (only) be accounted for from that point in time onwards. Thus, the fit of a model estimated by means of the Kalman Filter is at least comparable to, say, the fit generated by the OLS procedure.[3]

II. Model Specification

Following Barro (1977) and Mills et al. (1996), we will try to explain the Dutch unemployment rate as a function of its own lagged values, money supply, interest rate changes and an employment dispersion measure presented in Mills et al. (1996), which captures the sectoral shift hypothesis. This means that we

[1] See Mills et al. (1996) for an overview. Among the more recent publications is Fortin and Araar (1997).

[2] One may allege that since the years in which the revisions occurred are known, there is no special need to use a Kalman Filter approach. However, not only do the data come from different sources (as Appendix A indicates), but also are not all data revised in all years, which could lead to erroneous conclusions when using standard methods. Besides, the contents of certain variables are not comparable between revisions, so that the Kalman Filter technique probably yields results that are the least affected, for it does not ask for an exact specification of the revisions beforehand to produce results that in fact do take them into account.

[3] The OLS procedure is a special case of the Kalman Filter, cf. Watson (1983).

will mainly use data stemming from a monetary world to test the hypothesis. The interest rate variable and the money supply are included to capture the fact that inflation and monetary policies, if unexpected, influence unemployment duration. Expected policy changes are assumed to be covered by the lagged values of the unemployment rate. A constant term is also included in the analysis to catch some of the mean effects of other theories in the field (like the production function view described in Hamermesh and Grant (1979) and Pasinetti's (1981) view, stressing the learning power of individuals in a community). This does not mean however that without the constant term the model would be misspecified. Strictly speaking, it is not necessary to include it (and Mills et al. (1996) indeed do not). However, if we are considering to take a broader perspective than just monetary economic theory, the inclusion of a constant term can give a quick indication whether this broader view is justified.

The employment dispersion measure that is included may need some elaboration. Originally, Lilien (1982) proxied the dispersion of employment, $\hat{\sigma}_t$, by means of a weighted standard deviation variable using sectoral employment data:

$$\hat{\sigma}_t = \sqrt{\sum_i \left(\frac{x_{it}}{\sum_i x_{it}}\right)\left(\Delta \ln x_{it} - \Delta \ln \sum_i x_{it}\right)^2},$$

where, x_{it} = employment in sector i ($i = 1,2,\ldots,N$);
Δ = difference operator.

$\hat{\sigma}_t$ is calculated on the basis of the assumption that only sectoral shifts influence the dispersion of employment. However, employment dispersion can also be affected by aggregate shocks (which are also included in $\hat{\sigma}_t$). Therefore, Mills et al. (1996) proposed a method to eliminate these influences in $\hat{\sigma}_t$. Their method can be described as follows.

Suppose we have a regression model that contains $\hat{\sigma}_t$ (and possibly, its lagged values) among the explanatory variables. Each relative sectoral growth rate $\Delta x_{it} - \Delta(\sum_i x_{it})$ is then regressed on its own lagged value and current and lagged values of the other explanatory variables. The residuals of this regression, z_{it}, are then used to construct a revised dispersion measure $\hat{\sigma}_t^p$:

$$\hat{\sigma}_t^p = \sqrt{\sum_i \left(\frac{x_{it}}{\sum_i x_{it}}\right) z_{it}^2} \tag{1}$$

$\hat{\sigma}_t^p$ will enter our analysis as a measure of Lilien's sectoral shift hypothesis. In order to construct it, $\hat{\sigma}_t$ is regressed on its own lagged value and current and (once) lagged values of both the money supply variable and a (short-term) interest rate. Also, the current value of the GDP price level (with 1985 as the base year) is included in the regression to capture the influence of national commodity prices. 20 sectors are used in the analysis.[4] The residuals of this regression, estimated by OLS, enter the calculation of $\hat{\sigma}_t^p$ according to equation (1).

We start with a very broad model to explain the Dutch unemployment rate, which is gradually reduced to reach a ‘final’, smaller model. Insignificant variables and variables with incorrect signs are dropped one at a time, while testing for the (statistical) acceptability hereof by means of Likelihood Ratio tests.[5] A 5% level of significance is used. The following model is initially estimated:

$$\begin{cases} u_t = \begin{bmatrix} \beta_{0t} \\ \beta_{1t} \\ \beta_{2t} \\ \beta_{3t} \end{bmatrix} \begin{bmatrix} 1 \\ u_{t-1} \\ u_{t-2} \\ u_{t-3} \end{bmatrix} + \begin{bmatrix} \gamma_{0t} \\ \gamma_{1t} \\ \gamma_{2t} \\ \gamma_{3t} \end{bmatrix} \begin{bmatrix} M_t \\ M_{t-1} \\ M_{t-2} \\ M_{t-3} \end{bmatrix} + \begin{bmatrix} \delta_{0t} \\ \delta_{1t} \\ \delta_{2t} \\ \delta_{3t} \end{bmatrix} \begin{bmatrix} r_t \\ r_{t-1} \\ r_{t-2} \\ r_{t-3} \end{bmatrix} + \begin{bmatrix} \eta_{0t} \\ \eta_{1t} \\ \eta_{2t} \\ \eta_{3t} \end{bmatrix} \begin{bmatrix} \hat{\sigma}_t^p \\ \hat{\sigma}_{t-1}^p \\ \hat{\sigma}_{t-2}^p \\ \hat{\sigma}_{t-3}^p \end{bmatrix} + \varepsilon_t \\ \begin{bmatrix} \beta_{it} \\ \gamma_{it} \\ \delta_{it} \\ \eta_{it} \end{bmatrix} = \begin{bmatrix} \beta_{i,t-1} \\ \gamma_{i,t-1} \\ \delta_{i,t-1} \\ \eta_{i,t-1} \end{bmatrix} + \begin{bmatrix} v_{\beta_{it}} \\ v_{\gamma_{it}} \\ v_{\delta_{it}} \\ v_{\eta_{it}} \end{bmatrix} \end{cases},$$

[4] More details about the calculation of $\hat{\sigma}_t^p$ and a description of the data sources are presented in Appendix A.

[5] Tests based on a regular Wald statistic were carried out too, leading to identical results in the end.

where, u_t = (national) unemployment rate;
M_t = money supply (M_1);[6]
r_t = short-term interest rate;
$\hat{\sigma}_t^p$ = employment dispersion measure;
ε_t = random disturbance term;
i = 0,1,2,3.[7]

We assume the interest rate variables to be negatively related to unemployment, whereas the opposite is supposed for the money variables. All other variables can have either sign (although, leaving aside the constant term, positive signs are the most likely).

The 'final' model we end up with is, together with the corresponding OLS estimates, shown in Table 1 below. Because the observations over the period 1955-1961 are needed to estimate the so-called prior state vectors $ß_{i0}$, γ_{i0}, δ_{i0} and η_{i0} (which are constructed by OLS, and thus remain the same until 1962), the OLS estimates are confined to the period 1962-1993. This way, the comparability of the results is assured.

Before interpreting Table 1, we must verify that the Kalman Filtering mechanism that is employed withstands various specification tests. For example, is there significant multicollinearity present between the explanatory variables, which has influenced our final outcome? Or should we have started with a different model altogether? If this is correct, there is no need to interpret the results in Table 1, for they are not valid.

Watson (1983) proposes a small sample test to answer these questions, based on the properties of the one-step ahead prediction errors of the model (to be called π_t). They should be normally and independently distributed with mean zero and a variance equal to one. If the independence property is violated, the specification of the Kalman Filter is not optimal. We can resort to a Kolmogorov-Smirnov test to assess the standard normality of the prediction errors. In doing

[6] A narrow definition of money is used, cf. Pelloni (1992).

[7] All variables are lagged three periods following the work by Garcia-Ferrer et al. (1987).

Table 1. OLS and Kalman Filter Estimates of the 'Final' Model.

Coefficient	OLS (t-value)	Kalman Filter (t-value)	LR statistic (p-value)[8]
$ß_0$	-.245 (-.61)	1.019 (2.95)	-33.12 (1.00)
$ß_1$	1.789 (11.5)	.481 (1.84)	
$ß_2$	-1.159 (-5.69)	-.685 (-2.77)	
γ_1	.037 (3.76)	.093 (3.76)	
δ_0	-.035 (-.56)	-.251 (-1.12)	
η_1	26.97 (2.31)	101.1 (14.6)	
η_2	23.25 (2.43)	40.92 (4.07)	
$R^2_{adj.}$	.973	1.000	

Coefficients that do not appear in the Table were put to zero.

so, we can use two samples: one based on the entire estimation period (1955-1993) and one based on the period after the prior state vectors have been estimated (1962-1993). This last period is sometimes referred to as the period over which pure Kalman Filtering is performed.[9] Although for this reason, the latter period is to be preferred, we will present the outcome for both samples. Table 2 lists the relevant statistics.

Table 2 above tells us that the prediction errors π_t indeed follow a standard normal distribution (a 5% level of significance is used). Yet, hereby we have not tested the independence requirement. This is achieved by calculating the Pearson correlation coefficient between π_t and π_{t-1} (which is a valid approach for the

[8] As compared to the Kalman Filter estimates of the original model.

[9] See Watson (1983), p. 79.

normality of the data has been assessed)[10] for the two sample periods.[11] The results hereof are given in Table 3.

Table 2. Outcome of the Kolmogorov-Smirnov Test on the Standard Normality of the One-Step Ahead Prediction Errors of the 'Final' Model

Sample period	Kolmogorov-Smirnov test statistic (*p*-value)
1955-1993	.881 (.42)
1962-1993	.708 (.70)

Looking at Table 3, we see that the independence assumption of π_t is also satisfied. At a 5% level of significance we cannot reject the null hypothesis of zero correlation between π_t and π_{t-1} in either case. Nevertheless, an option that we still have not examined is that the one-step ahead prediction errors are biased.

Table 3. Pearson Correlation Coefficient between the One-Step Ahead Prediction Errors of the 'Final' Model at Period *t* and Period *t-1*

Sample period	Pearson correlation coefficient (*p*-value)
1955-1993	-.086 (.61)
1962-1993	-.086 (.64)

This may be the case because the basic assumptions underlying the Kalman Filter are highly restrictive: not only do the usual OLS assumptions have to be satisfied, but also should, among others, the initial prior state vectors $ß_{i0}$, γ_{i0}, δ_{i0}

[10] Spearman rank correlation coefficients were also calculated, leading to identical results.

[11] We only test for first-order autoregressive behavior of the prediction errors. Both Pearson and Spearman correlation coefficients for lags two through five were calculated too, yielding similar (insignificant) results.

and η_{i0} be known in advance. Since we do not know them, and OLS regressions are carried out to estimate their initial values, a certain amount of bias could have slipped through in our final results.[12] To test for this notion, we can use a standard *t*-test around the mean of the one-step ahead prediction errors π_t:[13]

$$\Theta = \frac{\bar{\pi}}{\hat{\sigma}_{\bar{\pi}}} \sim t_{N-1},$$

where, $\bar{\pi} = (1/N)\cdot\Sigma_i\pi_i$ $(i = 1,2,...,N)$.

Again, we have a choice between the two aforementioned sample periods. We will present the results achieved with both, as shown in Table 4.

Table 4. Testing the Bias of the One-Step Ahead Prediction Errors

Sample period	Θ (*p*-value)
1955-1993	.114 (.91)
1962-1993	.113 (.91)

Our conclusion is independent of the fact which sample period we choose: in both cases, there seems to be no bias around the mean of the prediction errors (using a 5% level of significance). Thus, the previously obtained results are statistically valid, so that we can start interpreting them.

[12] For this reason, one may claim that it would have been preferable to use the Kalman Smoother instead of the Kalman Filter right from the start. Then, we would estimate our model by means of the Kalman Filter for period 1 through *T*, and given these estimates, from period *T* to 1 and then the other way around again until the difference in estimates reached at stage *j* does not differ substantially from those at stage *j+1* (based on some criterion value). The estimates thus obtained are the steady state values of the model. However, the following test assesses whether these steady state values are sufficiently approximated by applying the Kalman Filter only once. If they turn out not to be, we will indeed have to turn to using the Kalman Smoother.

[13] Following Watson (1983), p. 78.

In doing so, let us go back to Table 1. There, it may be illuminating to see how the importance of the variables capturing the sectoral shift hypothesis has changed over time. Figure 1 contains graphs of the evolving state vectors of the η_1 and η_2 terms of the 'final' model.

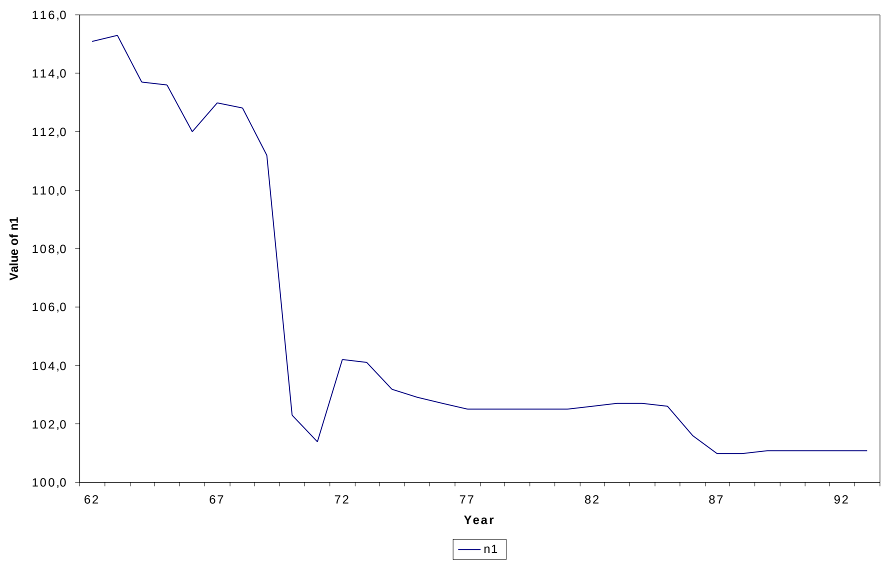
Judging from Figure 1, there appears to be a lot of volatility in the data (and thus, the size of the coefficients) of the 'final' model as far as the evolution of the sectoral shift variables is concerned. OLS, being more 'static' in nature by construction, fails to pick up these effects. The Kalman Filter framework that was adopted thus has its relevance, and we can rely on its estimates with more confidence than we can on the OLS results. Partly, the evolution of the Dutch unemployment rate is self-enforcing: two autoregressive terms turn up significantly in the 'final' model. It is interesting that these effects counteract with one another. Even stronger, the total effect is negative (leaving aside time subscripts).[14] The significance of the constant term points to the fact that using just monetary economic theory to explain the sectoral shift hypothesis may be a somewhat limited point of view, so that one might consider the inclusion of other variables in our model (for example, more macroeconomic oriented variables like wages or variables on union power). On the contrary, the insignificance of the constant term for the OLS estimates would imply that monetary economic theory alone may explain a sufficiently large part of Dutch unemployment behavior already.[15]

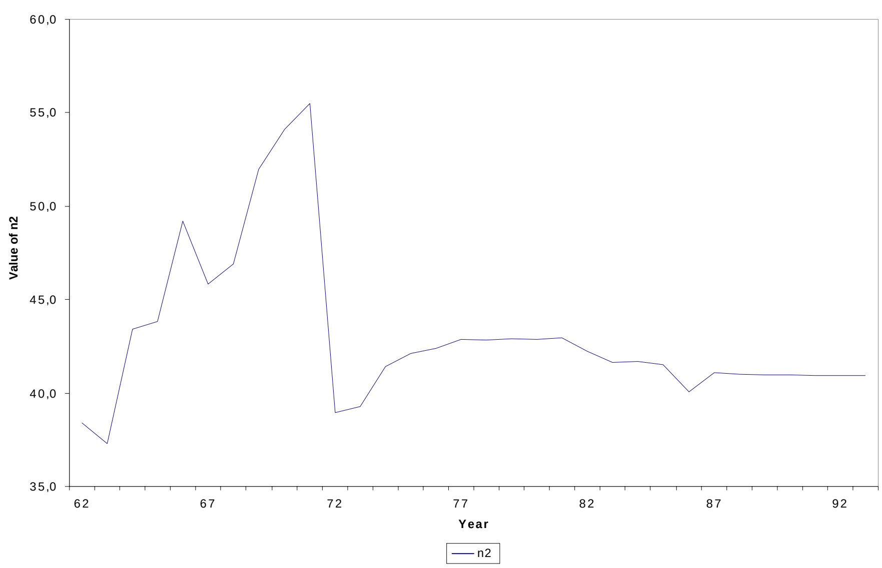
What is clear in any case, is that the statistically most important explanatory variables are the lagged employment dispersion measures. Thus, the sectoral shift hypothesis is endorsed. Moreover, given the evolution of the η_i variables over time, the role played by the hypothesis is definitely positive. As far as its relationship with the unemployment rate is concerned, we see that it is much stronger in the Kalman Filter approach than when applying OLS. Given that it is a weighted standard deviation variable, the magnitude of the estimates also indicates that the influence of sectoral shifts on Dutch unemployment behavior is quite massive. This result implies that policy makers should not limit themselves to aggregate models that do not explicitly incorporate a multisectoral dimension

[14] Which is appropriate if we were studying the long-term implications of our model.

[15] Certainly when looking at the $R^2_{adj.}$ value of .973.

Figure 1. Evolution of η_1 (Upper Graph) and η_2 (Lower Graph) over Time.





of (production and) employment when studying its behavior. The significant constant term in our model also indicates that non-monetary and non-fiscal policies can play a substantial role in stabilizing unemployment in the Netherlands.

III. Summary and Conclusions

The sectoral shift hypothesis was tested for the Netherlands in the postwar era using mostly monetary data, while adopting a Kalman Filter framework. We find evidence in support of the hypothesis. Nevertheless, it may very well be that the inclusion of other variables affecting unemployment (for example, more macroeconomic oriented variables like wages or variables on union power), would slightly alter the results. However, the examination hereof must be left for further research.

Appendix A. Data Description

The Dutch unemployment figures are taken from various sources at Statistics Netherlands (CBS) and Eurostat's SOCPROT database. They are all expressed in full-time equivalents (FTE). All Dutch employment data, which come from the Central Planning Bureau's (CPB) *LangeReeksen Boek 1950-1996*, have a similar base. Data on interest rates and the money supply are obtained from the IMF's *International Financial Statistics Yearbook* (from 1990 and 1995 publications). The GDP deflator is also contained herein, and is combined with comparable data from the OECD's STAN database. As a proxy of the short-term interest rate, the money market rate is used (which influences short-term borrowings between financial institutions).[16]

In order to calculate the employment dispersion measure $\hat{\sigma}_t$, we distinguished 20 sectors. These sectors are shown in Table 5 below. The time series $\hat{\sigma}_t$, that resulted using the employment information for the 20 sectors, subsequently entered the construction of $\hat{\sigma}_t^p$.

[16] As suggested by the IMF itself, cf. the *International Financial Statistics Yearbook 1995* (1995), pp. *xv-xvi*.

Table 5. Sectors Used in the Calculation of $\hat{\sigma}_t$.

Number	Description
1	Agricultural, forestry and fishery products
2	Food, beverage and tobacco
3	Textiles and clothing, leather and footwear
4	Wood, cork and furniture
5	Paper and printing
6	Chemical and rubber products, plastics
7	Metal products, machinery, office and data processing machines, electrical goods, precision and optical instruments
8	Petroleum and natural gas
9	Ferrous and non-ferrous ores and metals, minerals and mineral products (excluding petroleum and natural gas)
10	Production and distribution of electricity, gas, steam and (hot) water
11	Building and construction
12	Letting of real estate
13	Recovery and repair services, wholesale and retail trade services
14	Maritime and air transport services
15	Inland and auxiliary transport services
16	Communication services
17	Services of credit and insurance companies
18	Lodging and catering, other market services
19	Health care, other non-market services (excluding government services)
20	Government services

OLS regressions were carried out by the MicroTSP software package. The Kalman Filter estimates were calculated by TSP, while all specification tests were conducted in SPSS.

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