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Abstract:

This paper investigates the endogeneity of output in the context of the standard dynamic labour-demand model. Using a panel of Dutch firms, we find that the assumption of endogeneity of output cannot be rejected, so that an adjusted procedure has to be followed in which information on the output expectations of entrepreneurs is used. The estimated effect of the endogenous, current output variable on employment appears to be significantly larger than the effect of the exogenous, expected output variable. The adjustment parameter of employment is however, remarkably robust against distinct specifications for output.

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1. Introduction

Endogeneity is a genera1 problem in regression analysis, as it may lead to seriously biased estimates. In case of modelling the demand for labour, we are usually confronted with endogenous output, because employers decide on factor demand and output simultaneously. Yet, most empirical studies on labour demand simply ignore this problem. To get a proper understanding of the quality of such empirical analyses, it is important to get insight into the sensitivity of the estimates to the endogeneity of output. This issue has only seldomly been thoroughly examined.

It is noteworthy that Quandt and Rosen (1989) have investigated the endogeneity of output in a labour-demand equation and demonstrated that this phenomenon is not a serious problem. However, one may not conclude that their findings hold for any type of labour-demand model, since they only used a particular type of labour-demand model and a related specific data set; they analyse endogeneity of output in an equilibrium model of the labour market (as originally developed by Lucas and Rapping, 1970). The issue of endogeneity was not investigated for the nowadays important class of dvnamic labour-demand models (for an overview, see Hamermesh and Pfann, 1996). Furthermore, Quandt and Rosen used aggregate data, whereas many recently published empirical studies on labour demand use micro data on individual firms (for a survey of these studies, see Hassink, 1996).[1]

This paper analyses the endogenous output in labour-demand equations.. In contrast to Quandt and Rosens' approach, we will use a dynamic model as the major analytical framework and we will estimate this model by means of panel data. Another distinguishing feature of our analysis is that we will use information on the entrepreneurs' expectations on output. As far as we know, there are no studies available that use direct information on expectations about forcing variables such as output.[2]

To investigate the endogeneity of output we will concentrate on two questions. First, is output indeed an endogenous variable in a dynamic labour demand model? Second, how robust are the estimates to the endogeneity of output? It may happen that the endogeneity only gives a different estimate for the output coefficient only . In that case inferences on the remaining parameters (in particular the adjustment

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[1] Hamermesh (1992) points out that Quandt and Rosen do not provide solid evidence for the absence of endogeneity for firm-leve1 data.

[2] Ross and Zimmermann (1993) investigate the expected size of employment, but they have not incorporated expectations of output (due to data limitations).

parameter of employment) can still be made. A more serious case happens, if the endogeneity leads to differences between all estimated parameters of the equation. This means that the estimates lead to wrong conclusions in all respects. Thus, the endogeneity phenomenon may lead to serious statistical problems.

This paper is organised as follows. Section 2 discusses the dynamic labour-demand model. Section 3 offers the statistical model to be used in the present paper. In section 4 we will show the main features of the data, and in section 5 we will present the estimates. Section 6 will offer concluding remarks.

2. The labour-demand model

Entrepreneurs determine the amount of labour used by maximising their discounted profits. Following the standard dynamic labour-demand model we assume that the adjustment costs are quadratic and symmetric in upward and downward direction. Although this model is criticised on various points (Hamermesh and Pfarm, 1996) it is still widely used, for instance, to investigate time-varying adjustment costs (Anderson, 1993). According to the closed-form solution of the optimization problem the labour-demand equation at time t is (Nickell, 1986)

(1) $$L_t = \alpha L_{t-1} + (1 - \alpha)L^*_t,$$

where L is employment, L* is the desired value of employment, α is the adjustment parameter of employment, and where the index t represents time. In (1), L* is an infinite distributed lead on a vector of forcing variables X

(2) $$L_t = \alpha L_{t-1} + \Sigma_{s=0}^{\infty} \mu_s' E_t X_{t+s} + \varepsilon_t,$$

where E is the expectations operator and ε is an error term. The difficulty of (2) is the specification of the forcing variables at the RHS, because in empirical studies there is usually only limited information available. There are various possibilities to deal with this problem empirically .

An ideal data set would contain information on the employers' expectations about the future values of X. Then all variables in the dynamic labour-demand equation (2) are measured directly and proper estimates of the parameters can be obtained. As mentioned in the introduction, we are not aware of any studies that use direct information on expectations about the forcing variables.

If no information on the expected values of X is available then one needs to make assumptions about the underlying process through which employers form expectations. A usual assumption is that employers forecast only on the basis of past information on X. For instance, the forecasts at time t are based on the autoregressions

(3) $$E_t X_{t+s} = \rho_x^s X_t,$$

but it is also possible to use more general linear expressions based on previous values of X. Some empirical studies propose equations to forecast future values of X. A seminal time-series study of Nickell (1984) estimates the forecasting equations (3) simultaneously with labour demand (2). By means of so-called rolling regressions, Hamermesh (1989) constructs forecasts of output separately . This variable is then included as a regressor in the labour-demand model. It may be a problem to apply the method of rolling regressions for panel data with a short number of waves, because it is very difficult to get reliably predicted values. Another shortcoming is that the t-values of the estimated coefficient of the expected value are difficult to interpret (Pagan, 1984).

Instead of constructing forecasts of the forcing variables one may substitute (3) into (2) in order to obtain expressions of the form

(4) $$L_t = \alpha L_{t-1} + \Sigma_{s=0}^{S} \mu_s' X_{t-s} + \varepsilon_t.$$

Equation (4) is a widely used specification in empirical applications. Its drawback is the endogeneity of the output variable in X. It may give statistically biased estimates of all parameters. Surprisingly, several empirical labour-demand studies do not pay attention to the endogeneity of output. Some of these studies used macro data (see, e.g. Harvey et al., 1986), other studies are based on micro data (see, e.g. Bentolila and Saint-Paul, 1992) or on micro data extended with a current-output variable that is aggregated towards a narrowly-defined industry level (see, e.g. Anderson, 1993).

Endogeneity of output can be mitigated by simply excluding the current value of the independent variables. In that case specification (4) becomes

(4') $$L_t = \alpha L_{t-1} + \Sigma_{s=1}^{S} \mu_s' X_{t-s} + \varepsilon_t.$$

Note however that in (4') endogeneity of lagged output may still exist if the disturbances are serially correlated. According to Hamermesh' (1992) estimates there is a positive impact of the two-period lagged value of output on employment.

Another option is to instrument output with its lagged value. For instance, Bresson et al. (1992) use the current value and instrument this variable with some lagged values of output. One may wonder however, whether lagged output is a valid instrument, since it assumes implicitly that the correlation between the error term of the labour-demand equation and lagged output is zero.[3] According to estimates based on (4') there may exist a relationship between employment and lagged output. The instrumental estimates may be biased in case of a non-zero correlation between the lagged output and the error term.

In the remaining sections we will concentrate on the endogeneity of output. We will present and discuss the estimation results of (i) the standard model with current output, (ii) the IV-estimator of the standard model which uses lagged output as an instrument, and (iii) a specification which contains the expected-output variable.

3. The statistical model

This section discusses the statistical issues of our labour-demand model as specified in (2). Instead of a multi-period expectation we use a one-period forecast of X. Because of data limitations (see Section 4), we reduce the vector of forcing variables X to the real-output variable Y.[4] For firm i the empirical labour-demand model at time t is

$$(5) \qquad l_{i,t} = \tau_i + \alpha l_{i,t-1} + \mu E_t y_{i,t+1} + \varepsilon_{i,t},$$

with

$$\begin{aligned} E\varepsilon_{i,t} &= 0 & & \\ E\varepsilon_{i,t}\varepsilon_{j,s} &= \sigma_i^2 & & \text{if } i = j, \\ & & & \quad t = s \\ &= 0 & & \text{elsewhere} \end{aligned}$$

τ_i is a firm-specific parameter. The lower-case letters l and y are used to denote the natural logarithm of L and Y respectively.

To remove τ_i we take the first difference of (5)

[3] Also from a more historical perspective on labour demand this assumption is very peculiar. In the original labour demand studies the correlation was expected to be non-zero. These labour studies with adaptive expectations assumed that the expected (or desired) employment is a factor in the production function.

[4] Output gives sufficient information on the forcing variables X (see Hamermesh, 1989).

(6) $$\Delta l_{i,t} = \alpha\Delta l_{i,t-1} + \mu\Delta E_t y_{i,t+1} + \Delta\varepsilon_{i,t},$$

where A is the difference operator. Because of the correlation between $\Delta l_{i,t-1}$ and $\Delta\epsilon_{i,t}$ we instrument $\Delta l_{i,t-1}$ by l_{t-2}. Furthermore, the error term $\Delta\epsilon_{i,t}$ is by definition serially correlated of an Moving Average (1) type. We use Genera1 Methods of Moments (GMM) to estimate equation (6) which eliminates autocorrelation, allows for heteroscedasticity and provides consistent and efficient estimates (see Chamberlain (1992) and Hayashi (1992).

Equation (6) is the baseline specification, since it does not contain any endogeneity of output. To test for the presence of endogeneity of output we will include both the expected and the realised value of output in the labour-demand equation

(7) $$\Delta l_{i,t} = \alpha\Delta l_{i,t-1} + \mu_1\Delta E_t y_{i,t+1} + \mu_2\Delta y_{i,t} + \Delta\varepsilon_{i,t},$$

A significant coefficient μ_2 of the current output variable indicates that there is some endogeneity of output.

To examine the robustness of the estimates with respect to the endogeneity of output we will compare the estimate of (6) with the estimate of

(8) $$\Delta l_{i,t} = \alpha\Delta l_{i,t-1} + \mu\Delta y_{i,t} + \Delta\varepsilon_{i,t}.$$

The differences between the estimated parameters of (6) and (8) may reveal the sensitivity of the estimates to endogeneity of output.

4. Data

Each year the Dutch Chambers of Commerce hold a survey among all Dutch firm establishments with at least 50 employees, while a random sample of about 50% is drawn from the establishments having less than 50 employees (establishments without employees are not addressed).[5] We denote these establishments by firms. For the years 1986-1994 we have access to the survey data on the districts Amsterdam, Utrecht and Den Bosch. The average number of firms in each of the districts is 1250, 1344 and 1133, respectively. These districts can be considered to be

[5] The economic sectors are agriculture, industrial, construction, wholesale, retail and services.

representative for the core area of the Dutch economy (see Nijkamp et al., 1992).

We constructed unbalanced panels for each year (during 1987-1994) by matching each individual firm in each two subsequent surveys (cross-sections or waves). It appears that about 50% of the companies which fills in the questionnaire in year t also responds in year t + 1.

Each wave contains information on firm characteristics such as employment, output and so on. Employment is measured as the number of employees who work in the firm for at least 15 hours a week. In each wave the firm's employment level is asked for both the current and the previous year. The firm's current-output level is measured by using questions on the output-growth rate (reported in percentages) for the current year[6] and the output level in the previous year. The latter variable is a mixed continuous-discrete variable: when output is less than 10.000 or more than 10.000.000 Dutch guilders its precise level is not reported but it is indicated to which class the level belongs (in that case we used the mid-point of the class). Next, we deflated the output level for the current period by the OECD producer price index of the output. In each wave, firms are also asked to report their employment and output expectations for the next year. In particular, they are asked to provide qualititative information. The specific formulation of the question with respect to output is "Compared to this year, will next year output be higher (higher than 2% growth), equal (between 0-2% growth) or lower (less than 0% growth)? So, instead of a continuous variable $E_t y_{t+1}$, we use two dummy-variables: $E_t DY^-_{t+1}$ is 1, if the nominal output is expected to be lower in the next year, and 0 elsewhere; $E_t DY^+_{t+1}$ is 1, if the nominal output is expected to have increased with more than 2% (to account for inflation) next year and 0 elsewhere. Thus, constant output expectation (between 0-2% growth) will be used as the reference group.

In Table 1 the average values of the employment and output variables used in our model are presented for each year together with the standard deviation (of the mean), based on our panel data. Both output and employment change reached their maximum value around the year 1989-1990. The minimum value was reached in 1993, when both were negative. We also observe that employment and output change follow the same pattem, though output exhibits larger fluctuations over time. Table 1 also includes information on a pooled panel-data set (i.e., taking all separate panels together).

Since it is also possible to compute growth rates from each separate wave (due

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[6] It is noteworthy that the output realisations are reported during the current year (in the months September-November), so that this variable has - to a very limited extent - a predictive nature.

to the retrospective information on employment and output), we were able to verify whether the picture of employment growth and output growth (based on separate waves) is different from our panel data. This does not appear to be the case, so that there does not appear to be a selection effect when two subsequent surveys are combined. Moreover, when we confront at the individual level the growth rates as provided in a particular wave (based on retrospective data) with growth rates based on the levels reported in two subsequent waves we do not observe significant differences.

[Table 1 about here]

Furthermore, Table 1 presents the percentage of positive and negative cases in our panel data for the current and expected output. These percentages are quite stable over time. Only the year 1993 shows some different outcomes. Compared to the year before, the percentage of firms that show a decline in output has increased with 12 percent-points, while the percentage of firms that shows an increase in output has decreased with 10 percent-points. Moreover, the percentage of firms that expects a rise in output decreases, while the percentage of firms that expects a decline in output remains relatively constant. Al, Al,, and Ay became apparently negative in 1993. In 1994, the figures return towards their values obtained in the period 1987-1992. It is also interesting to see that the percentage of firms that expects an output decline is - on average - about 10 percent-points lower than the percentage of firms faced with a realised output decline. Apparently , the group of firms as a whole is rather optimistic as far as their expectations on output decline is concerned .

5. Empirical results

5.1 The presence of endogeneity of output

Before we test for the presence of endogenous output we first apply the "traditional" estimation procedure of the standard dynamic labour-demand model (based on the labour demand model shown in (4)). Then we are able to compare these estimates with the estimation results of previous empirical studies.

As demonstrated in (8), one can ignore the problem of endogeneity of output completely by including a current output variable instead of expected output. Table 2 gives the GMM estimates of this model for each panel (year) separately and for the pooled panel data set (i.e. taking all years together).[7] We observe that over the years the estimated adjustment parameter (α) falls in the range of 0.2-0.5, while the elasticity of employment with respect to output μ is usually inside the range of 0.3-0.5. Surprisingly , we find remarkably different outcomes for the year 1993. The adjustment process (as reflected by the estimate for α) appears to be extremely slow and the response to current-output developments is much weaker. We checked whether this unexpected finding is due to outliers in our data, but this does not appear to be the case.[8] Exclusion of the year 1993 in the pooled model gives about the same estimates for α and μ.

[Table 2 about here]

Compared to previous studies, the estimate of 0.28 for α impiies a rather fast adjustment. It implies that the median length of the lag (the time it takes to move halfway in response to a shock) is about 2 quarters of a year. According to a survey of Hamermesh (1993) this period is on average 5.5 quarters for studies with annual data.

The estimated parameters on α and μ incorporate also information on the returns to labour (s). In our specification of the model, we have:

$$s=\frac{\mu}{1-\alpha}$$

so that our estimate of s in the pooled model is about 0.6. According to a survey of Hamermesh (1993) most empirical studies have found increasing returns to labour in the production function (s < 1). In his survey of 101 studies he finds an average estimate of about 0.8, which reduces to 0.6 for studies based on firm-level data.

Table 3 about here

[7] It turns out that our GMM estimates are hardly different from those estimated by using FD (First Differences)-2SLS. In particular, the correction made to allow for a moving average structure (MA(l)) of the error terms (see also equation (5)) has no impact on the outcomes at all, while allowing for heteroscedasticity basically only leads to a substantial change in the standard error of the 'current-output' effect.

[8] First, we eliminate the most "extreme" observations in 1993 on the basis of the residuals from a first-run estimate, and then re-estimate the model for the reduced sample size. The parameters values are however, unaffected by this procedure.

As discussed in Section 2, it is likely that the effect of realised output is unreliable due to the simulteneity of employment and current output. To cope with endogeneity of current output in (8) we have instrumented current output with its lagged value. Table 3 presents the result of this method. In comparison with the previous results (in which current output was assumed to be exogenously determined), we find a somewhat lower - but not significantly different from the value obtained before - value of α (equal to 0.21) and a much higher value for μ (equal to 0.62). As a result, the returns to labour is about equal to 0.75. In addition, the overall fit of this model appears to be better than the model with the current-output value. Note also that the rather unusual result for 1993 vanishes when we instrument output with its lagged value (α becomes equal to 0.36).

Although the estimation results with lagged output (y_{t-2}) as an instrument for Δy_{t-1} look quite satisfactory, we have to re-emphasize that we may stil1 be confronted with biased estimates of the parameters of interest. As discussed in Section 2 these biases will occur when the instrument chosen for output, namely the lagged value of output, is not valid. The validity of this instrument is tested by regressing the first difference of current employment on the (double) lagged value of output (y_{t-2}).[9] The estimate clearly shows a significant relationship, which implies that we cannot rely on the estimates with lagged output (y_{t-2}) as an instrument.

To test for the presence of endogeneity of output we make use of the expected output variable ($E_tDy^-_{t+1}$ and $E_tDy^+_{t+1}$) as described in Section 4. We include this discrete variable along with actual output in the same labour demand equation (see also (7)). As mentioned in Section 3 a significant coefficient of current output indicates that endogeneity is present. Table 4 gives the estimation results. The estimates of the coefficient of current output are almost equal to those of Table 2. In spite of the inclusion of the expected output dummies the coefficient of the current output variable is stil1 strongly significant. We conclude that the endogeneity of (current) output cannot be rejected.

Table 4 about here

5.2 The robustness of the estimates to the endogeneity of output

This subsection investigates the sensitivity of the estimates to the endogeneity of

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[9] The estimated coefficient and its t-value are 0.002 and 10.85 in the pooled model, respectively . Note also that we also obtain significant effects of the lagged value of output in the models for the separate years.

output. We compare the coefficients of the labour-demand models with either output expectations or output realisations included (equations (6) and (8)). To make a direct comparison possible between the effects of current output and expected output, we have constructed a more “condensed” current output variable (Dy_t^- and Dy_t^+), i.e. a discrete output variable with classes similar to the categories of the expected output variable ($E_tDy^-_{t+1}$ and $E_tDy^+_{t+1}$). The estimation results are presented in Tables 5 and 6, respectively.

Tables 5 and 6 about here

Tables 5 and 6, show that - in most years - the estimated effects of current output are <u>larger</u> in absolute size than the effects of expected output. According to the estimates for the pooled data set, the effect of current-output developments is significantly different from the effect of expected output developments (about twice as large: -0.07 (0.002) versus -0.04 (0.005) in case of a negative output-shock and 0.05 (0.002) versus 0.03 (0.002) in case of a positive output shock).”

Another important observation concerns the robustness of the adjustment parameter α against the various specifications used for output (see Table 7).

Table 7 about here

Although the estimated parameters for output (μ) differ, the estimates for the adjustment parameter (α) are hardly affected (within the range 0.2-0.3). This implies that when one is interested in the speed of the adjustment process of employment by means of labour-demand models, one need to worry less about the potential exogeneity of output in these models. However, when the focus is also on the output effect itself (employment elasticity with respect to output) and the returns to labour, one cannot ignore the endogeneity problem. Both μ and s are apparently sensitive to the way output is incorporated in the dynamic labour-demand model.

6. Conclusions

In this paper we have estimated the parameters of a standard dynamic labour-demand model that allows for autocorrelation and heteroscedasticity by using a Genera1 Methods of Moments technique.

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[10] For the separate years, we observe that the confidence intervals for the corresponding output estimates are partially overlapping in most cases.

We have tested whether the potential endogeneity of output is present by including both the expected output variable (as provided by entrepeneurs) and the current output variable in the same labour demand equation. It appears that the coefficient of current output is strongly significant implying that the endogeneity of current output cannot be rejected in the context of a dynamic labour demand model.

Therefore, to measure the impact of output on employment properly , one needs information on the output expectations of entrepreneurs. This implies that one needs either information on the expected output or forecasts that are constructed by means of a forecasting equation. The drawback of the latter method is that it is not always possible to construct proper forecasts, for instance, in case of panels with a short time span. Our result is opposite to that of Quandt and Rosen, who concluded - on the basis of aggregate data - that endogeneity of output is not a serious problem within the framework of a static labour demand model. Of course, we have to stress that our rejection of endogeneity of output is related to a particular analytical framework as well; our conclusion only holds for the standard dynamic labour-demand model with symmetric and quadratic adjustment costs. Further research should indicate whether endogeneity of output is also a problem in labour-demand equations based on asymmetric or lumpy adjustment costs.

We have also investigated the sensitivity of the estimates to the endogeneity of output. It appeared that the estimated effect of current output is significantly larger in absolute size than the effect of expected output. On the other hand we have found that the adjustment parameter is remarkably robust against the distinct specifications used for output. Although there are differences in the estimated parameter for expected or realised output, the estimates for the adjustment parameter are hardly affected. Hence when one is interested in the speed of the adjustment process of employment by means of the standard labour-demand model, one need to worry less about the endogeneity of current output in these models.

References

Anderson, P.M. (1993), "Linear Adjustment Costs and Seasonal Labor Demand: Evidence from Retail Trade Firms," Quarterlv Journal of Economics, 108, 1015-1042.

Bentolila, S., and Saint-Paul, G. (1992), "The Macroeconomic Impact of Flexible Labour Contracts, an Application to Spain," European Economic Review, 36, 1013-1053.

Bresson, G., Kramarz, F., and Sevestre, P. (1992), "Heterogeneous Labour and the Dynamics of Aggregate Labour Demand: Some Estimations Using Panel Data," Emnirical Economics, 17, 153-168.

Chamberlain, G. (1992), "Comment: Sequentia1 Moment Restrictions in Panel Data," Journal of Business and Economic Statistics, 10, 20-26.

Hamermesh, D.S. (1989), "Labor Demand and the Structure of Adjustment Costs," American Economic Review, 79, 674-689.

Hamermesh, D.S. (1992), "A Genera1 Model of Dynamic Labor Demand," Review of Economics and Statistics, 74, 733-737.

Hamermesh, D. S . (1993), Labor Demand, Princeton: Princeton University Press.

Hamermesh, D.S., and Pfann, G.A. (1996), "Adjustment Costs in Factor Demand," Journal of Economic Literature, Forthcoming .

Harvey, A.C., Henry, S.G.B., Peters, S., and Wren-Lewis, S. (1986), "Stochastic Trends in Dynamic Regression Models: an Application to the Employment-Output Equation, " The Economic Journal, 96, 975-985.

Hassink, W.H.J. (1996), Worker Flows and the Emnlovment Adiustment of Firms; an Emnirical Investigation, Dissertation Free University Amsterdam, Tinbergen Institute Research Series, no. 105.

Hayashi, F. (1992), "Comment," Journal of Business and Economic Statistics, 10, 15-17.

Keane, M.P., and Runkle, D.E. (1992), "On the Estimation of Panel-data Models with Serial Correlation when Instruments are not Strictly Exogenous," Journal of Business and Economic Statistics, 10, 1-9.

Lucas, R., and Rapping, L. (1970), "Real Wages, Employment and Inflation," in E. Phelps (eds), Microeconomic Foundations of Emplovment and Inflation Theory. New York: Norton.

Nickell, S.J. (1984), "An Investigation of the Determinants of Manufacturing Employment in the United Kingdom," Review of Economic Studies, 51, 529-557.

Nickell, S. J. (1986), "Dynamic Models of Labour Demand," in Handbook of Labor Economics, eds. O.C. Ashenfelter and R. Layard, Amsterdam: North-Holland.

Nijkamp, P., Rouwendal, J. and Van der Ende, M. (1992), "Space-time Patterns of Enterpreneurial Expectations and Performance, " Regional Studies, 1-11.

Pagan, A. (1984), "Econometric Issues in the Analysis of Regressions with Generated Regressors," International Economic Review, 25, 221-247.

Quandt, R.E., and Rosen, H.S. (1989), "Endogenous output in an Aggregate Model of the Labor Market, " Review of Economics and Statistics, 71, 394-400.

Ross, D .R. and Zimmermann, K.F. (1993), "Evaluating Reported Determinants of Labor Demand," Labour Economics, 1, 71-84.

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Tabel 1, *Means of **the** variables*[a)].

	Al	Δl_{t-1}	Δy	DY,	DY+,	$E_tDy^-_{t+1}$	$E_tDy^+_{t+1}$
1987	0.02 (0.004)	0.02 (0.006)	0.01 (0.003)	26%	44%	11%	39%
1988	0.03 (0.003)	0.04 (0.006)	0.03 (0.002)	15%	41%	7%	40%
1989	0.03 (0.003)	0.04 (0.006)	0.03 (0.002)	13%	43%	6%	44%
1990	0.03 (0.003)	0.04 (0.006)	***0.04*** (0.003)	13%	44%	8%	42%
1991	0.02 (0.003)	0.04 (0.005)	0.02 (0.002)	18%	38%	9%	42%
1992	0.01 (0.003)	0.03 (0.005)	0.01 (0.002)	19%	36%	14%	37%
1993	-0.01 (0.003)	-0.01 (0.005)	-0.02 (0.003)	31%	26%	13%	29%
1994	-0.01 (0.003)	-0.02 (0.006)	***0.00*** (0.003)	22%	32%	10%	37%
pool	0.01 (0.001)	0.02 (0.002)	0.01 (0.001)	19%	38%	10%	39%

a) For the data in the separate years and the pool (1987-1994), the means of the dependent (Al) and the explanatory variables (Al,, and Ay) are reported, together with the standard error of the mean. In the pooled dataset the average number of employed (L, in persons) is equal to 37 (standard error equal to 96) in the current year and 36 (95) in the previous year, whereas the average output in thousands of guilders is equal to 17503 (94777).
DY^-_t and DY+, are dummies for realised output decline and growth at time t; $E_tDY^-_{t+1}$ and $E_tDY^+_{t+1}$ are the dummies for forecasts at time t for the output growth and decline in year t+ 1. For the dummy variables the percentage of positive and negative cases is reported.

Table 2, GMM-estimates of the labour-demund model".

dependent ↓	Δl_{t-1}	Δy_t	SE SSR	n
Δl_{87}	0.46 (2.64)	0.52 (8.76)	0.23 138.74	2528
Δl_{88}	0.35 (4.11)	0.46 (6.77)	0.22 153.02	3287
Δl_{89}	0.24 (3.17)	0.54 (9.15)	0.18 112.26	3355
Δl_{90}	0.24 (2.95)	0.45 (9.05)	0.20 142.49	3634
Δl_{91}	0.26 (3.88)	0.30 (7.48)	0.19 148.08	4146
Δl_{92}	0.20 (3.16)	0.45 (7.56)	0.19 173.24	4652
Δl_{93}	0.73 (4.10)	0.21 (2.94)	0.30 345.91	3866
Δl_{94}	0.39 (5.29)	0.36 (8.69)	0.23 184.99	3552
pool[b]	0.28 (7.88)	0.40 (17.26)	0.20 1007.80	24998"

a) t-values in parentheses, Al,, instrumented with l(-2).

b) Year dummies are included.

c) The pool consists of the full sample for 1987 and random samples (of 3210 cases) drawn from subsequent years; this sampling procedure was needed due to computational constraints on the number of cases when using GMM (in TSP). To check for the robustness of the results we have rerun the above mentioned sampling procedure several times (i.e., taking different random samples from 1988-1994 of 3210 observations), but this tumed out to have no impact on the estimated parameters.

Table 3, GMM-estimates of the labour-demund model".

dependent ↓	Δl_{t-1}	Δy_t	SE SSR	n
Δl_{87}	0.32	0.95	0.22	2528
	(3.13)	(2.82)	123.61	
Δl_{88}	0.17	0.58	0.19	3287
	(3.71)	(5.85)	113.05	
Δl_{89}	***0.08***	0.72	0.16	3355
	(1.69)	(9.33)	90.85	
Δl_{90}	0.20	0.68	0.20	3634
	(3.78)	(7.50)	140.53	
Δl_{91}	0.13	0.78	0.19	4146
	(2.73)	(4.77)	147.44	
Δl_{92}	0.23	0.27	0.20	4652
	(4.80)	(1.16)	184.89	
Δl_{93}	0.36	0.60	0.22	3866
	(5.42)	(5.21)	185.36	
Δl_{94}	0.29	-0.05	0.22	3552
	(4.24)	(-0.15)	176.19	
pool[b]	0.21	0.62	0.19	24998"
	(9.45)	(7.74)	919.40	

a) t-values in parentheses, Al,, instrumented with l(-2), Δy_t instrumented with y(-2).

b) Year dummies are included.

c) See remark made at point (c) in Table 2.

*Table 4, GMM-estimates **of the** labour-demand **model** with current and expected output"'.*

dependent ↓	Δl_{t-1}	Δy_t	$E_tDY^-_{t+1}$	$E_tDY^+_{t+1}$	S E SSR	n
Δl_{87}	0.40 (2.31)	0.48 (7.70)	-0.01 (-0.74)	0.02 (1.78)	0.22 124.89	2528
Δl_{88}	0.33 (3.79)	0.44 (6.08)	***-0.00*** (-0.12)	0.01 (0.89)	0.21 147.99	3287
Δl_{89}	0.19 (2.55)	0.45 (7.21)	-0.01 (-0.84)	0.02 (2.87)	0.17 101.74	3355
Δl_{90}	0.18 (2.38)	0.40 (7.75)	-0.01 (-0.55)	0.02 (2.44)	0.19 128.35	3634
Δl_{91}	0.18 (2.72)	0.29 (7.58)	***-0.00*** (-0.37)	0.01 (2.32)	0.18 132.81	4146
Δl_{92}	0.21 (3.32)	0.46 (6.73)	-0.02 (-1.53)	0.00 (0.18)	0.19 176.00	4652
Δl_{93}	0.76 (4.00)	0.20 (2.73)	-0.01 (-0.89)	0.01 (0.73)	0.31 360.62	3866
Δl_{94}	0.34 (4.68)	0.37 (8.67)	-0.03 (-1.93)	-0.01 (-1.11)	0.22 170.17	3552
pool[b]	0.24 (7.44)	0.39 (17.86)	-0.01 (-2.61)	0.01 (3.77)	0.19 941.50	24998'

a) t-values between parentheses, Al,, instrumented met l(-2).

b) Year dummies are included.

c) See remark made at point (c) in table 2.

***Table 5,** GMM-estimates of the labour-demund model with current output as a discrete variable*[a)].

dependent ↓	Δl_{t-1}	DY,	DY+,	SE SSR	n
Δl_{87}	0.33 (1.74)	-0.06 (-5.41)	0.06 (6.36)	0.22 123.22	2528
Δl_{88}	0.32 (3.70)	-0.07 (-5.80)	0.06 (8.38)	0.22 152.63	3287
Δl_{89}	0.19 (2.47)	-0.08 (-6.77)	0.07 (10.94)	0.18 108.18	3355
Δl_{90}	0.16 (2.17)	-0.08 (-6.41)	0.07 (10.47)	0.19 132.12	3634
Δl_{91}	0.26 (3.48)	-0.06 (-7.60)	0.04 (6.29)	0.19 152.39	4146
Δl_{92}	0.24 (3.66)	-0.08 (-8.74)	0.05 (11.13)	0.21 197.09	4652
Δl_{93}	0.68 (4.07)	***-0.05*** (-5.02)	0.04 (3.88)	0.29 318.16	3866
Δl_{94}	0.26 (4.28)	-0.08 (-8.02)	0.03 (5.44)	0.21 157.86	3552
pool[b]	0.26 (7.72)	-0.07 (-18.85)	0.05 (21.80)	0.20 1028.88	24998"

a) t-values in parentheses, Al,, instrumented with l(-2).

b) Year dummies are included.

c) See remark made at point (c) in Table 2.

*Table 6, **GMM-estimates of** the **labour-demand** model with expected output*^{a}.

dependent ↓	Δl_{t-1}	$E_tDY^-_{t+1}$	$E_tDY^+_{t+1}$	SE SSR	n
Δl_{87}	0.46 (2.48)	-0.06 (-2.51)	0.04 (4.62)	0.25 153.98	2528
Δl_{88}	*0.29* (3.30)	-0.02 (-1.71)	0.04 (4.90)	0.21 150.22	3287
Δl_{89}	0.15 (1.93)	-0.04 (-2.88)	0.06 (9.75)	0.18 107.11	3355
Δl_{90}	0.20 (2.53)	-0.02 (-1.64)	0.05 (7.25)	0.20 144.49	3634
Δl_{91}	0.21 (2.93)	-0.02 (-2.27)	0.03 (4.58)	0.19 144.98	4146
Δl_{92}	0.23 (3.48)	-0.04 (-4.05)	0.02 (4.46)	0.21 203.53	4652
Δl_{93}	0.88 (4.51)	-0.03 (-1.64)	0.01 (0.91)	0.34 449.39	3866
Δl_{94}	0.30 (4.12)	-0.06 (-4.13)	0.01 (0.88)	0.22 173.36	3552
pool[b]	0.27 (7.79)	*-0.04* (-7.87)	0.03 (13.08)	0.21 1079.19	24998[c]

a) t-values in parentheses, Δl_{t-1} **instrumented** with l(-2).

b) Year dummies are included.

c) See remark made at point (c) in Table 2.

Table 7, ***Estimates of α, μ and s across different model specifications within the framework of the standard dynamic labour-demand model***[a]

Model	Output	Adjustment parameter (α)	Employment elasticity (μ)	Returns to labour (s)
Ia	current value	0.28 (0.036)	0.40 (0.023)	0.55
Ib	current value, instrumented with lagged output	0.21 (0.022)	0.62 (0.081)	0.75
Ic	current value, measured as discrete variable	0.26 (0.034)	about 0.4[b] (DY-: -0.07 DY+: 0.05)	about 0.55
II	expected value, measured as discrete variable	0.27 (0.035)	about 0.2[c] (DY.: -0.04 DY+: 0.03)	about 0.27

a) Standard errors in parentheses.

b) Estimate for μ is based on Model Ia

c) The estimates of the dummies in the model with expected values for output are about half of the estimated parameters in the model based on realised output.