Sources of asymmetry in production factor dynamics

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Abstract

In this paper we investigate possible sources of aggregate cyclical asymmetry of production factor dynamics using a trivariate structural dynamic model of capital and labor demand and output. The two sources are: internal or behavioral asymmetry resulting from asymmetry in costs of adjusting factor inputs, and external non-linearity present in the process of real factor prices, being the model's forcing variables together with productivity shocks. In the empirical analysis behavioral asymmetry and external non-linearity are disentangled by estimation (GMM) and by simulation techniques. Simulated solutions of the model's nonlinear first order necessary conditions are obtained using an extended version of the parameterized expectations algorithm (PEA). Behavioral asymmetry accounts for about 50 percent of the curvature of adjustment costs and therefore contributes in an important way to the dynamics of production factors; external non-linearity on the contrary plays only a moderate role. © 1997 Elsevier Science S.A.

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"Asymmetry of waves, i.e. the fact that the upward movement is generally slower than the downward, [...] may be attributed to the fact that the production lag is larger during the expansion than during contraction".


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1. Introduction

We see no reason why the marginal costs of increasing factor inputs would be the same as those of an equal size decrease.\footnote{This symmetry is implied by dynamic factor productivity models that use linear-quadratic forms for production technologies and adjustment costs. In this strand of literature adjustment costs are considered to be the most important source of quasi-fixedness of production factors. Early examples in the literature are Hansen and Sargent (1980) and Meese (1980).} Symmetry and other implications of linear-quadratic dynamic models of factor demand frequently failed to pass statistical tests. Successful attempts to overcome the problem of misspecification, generalizing the functional form of production technologies, were initiated by Morrison and Berndt (1981) and Pindyck and Rotemberg (1983). The generalized production functions, however, were often incorporated in static models or in models with linear-quadratic – internal – adjustment costs. The quadratic shape of the dynamics propagation mechanism that was put forward initially as a first and kept later on as a convenient approximation, turned out to be one of the true binding constraints to match modern dynamic macroeconomic theory with the – aggregate – data.

If upward changes are more costly, not only will it take longer for factor inputs to go up from a trough to a peak, but the troughs will be deeper as well. What we do know now is that positive adjustments in factor input utilization (their sources) may differ in magnitude (their structures) and duration (their sizes) from downward ones.\footnote{See Neftçi (1984) and Hussey (1992) on evidence of asymmetry and duration dependence in US unemployment rates and aggregate employment; Abel and Eberly (1994) present a unified nonlinear model for capital investments; Pfann and Palm (1993) present a new model and empirical evidence for asymmetry in workforce changes for heterogeneous types of workers.} But nonlinear laws of motion usually prevent analytical closed-form forward looking solutions to be derived from first-order necessary conditions and make elasticities difficult to compute. The implications of the fact that the linear-quadratic assumptions are not supported by the data at the aggregate level\footnote{See Peck (1974) for a remarkable early study of capital investments in the electric utilities industries and Pfann and Verspagen (1989) for the costs of employment adjustment for individual firms.} nor at the firm level\footnote{See Hamermesh and Pfann (1996a).} can be quite substantial. For example, Pfann (1996) showed that the differences in total adjustment time between contractions and expansions in Dutch and UK manufacturing can be as large as 18 months for labor and 27 months for capital. What we do not know is how we should change the way we think about the dynamics of aggregate factor productivity in the light of those new insights. Important questions that arise are: What are the sources of the asymmetries? And, more generally, why do all the tests for the underlying structures of adjustment costs matter for the
aggregate dynamics of production factors? These questions will be addressed in this paper. Correct answers should be relevant to improve our ability to predict production factor dynamics; they should also lead to a firmer and sounder embedding of dynamic models of factor productivity in economic theory.

The aim of this paper thus goes some steps beyond the specification and estimation of production technologies and nonlinear dynamic optimization rules by instrumental variables methods as initially proposed by Kennan (1979). The question that remains unanswered by the mere estimation of the structural parameters, is which sources of asymmetry contribute most to the shape of the factor input cycles. To investigate that question, we solve a nonlinear rational expectations model using an extended version of the parameterized expectations algorithm (PEA) put forward by Den Haan and Marcet (1990) and Marcet and Marshall (1994). When we completely specify the generating processes of the model's forcing variables, the PEA solution method enables us to identify the importance of the two possible sources of asymmetry in factor input dynamics that we consider in this paper. One source is behavioral or internal asymmetry (asymmetry in the propagation mechanism) that results from facts that are typically incorporated in what is stated as the costs of adjustment (cf. Hamermesh and Pfann, 1996a). The second source considered is external non-linearity that is induced by the variables that drive the model. External non-linearity could, for example, be due to nonlinear pricing rules, including for example downward rigidities, or to asymmetrically distributed taste or productivity shocks. The differences between those two possible sources are important because the first, behavioral, source is partly endogenous and can be controlled by the firm, while the second, external, source cannot. The estimates of the model's structural parameters are based on undetrended seasonally adjusted quarterly time series data of the Netherlands manufacturing sector for the period 1971.I–1990.IV. Economic growth is a common trend that results from accumulated productivity shocks.

We find that behavioral asymmetry, resulting from asymmetric adjustment costs, contributes substantially to the non-linearity of factor input dynamics: 53% of the total second-order effect for capital and 48% for employment is accounted for by behavioral asymmetry. Our analysis shows that the significance of this finding is not simply an artefact due to the presence of external non-linearity. It is an important structural phenomenon that has to be accounted for when analyzing factor input dynamics at an aggregate level.

Nonlinearity in the driving variables possibly leads to a nonstationary and nonergodic process for the endogenous variables and thereby invalidate the conditions under which the asymptotic properties of the GMM estimator were derived. The robustness of our results is investigated on the basis the model's simulated solutions by the PEA method: the simulated finite sample distributions of the structural parameter GMM estimates under different regimes and the finite sample properties of the Sargan–Hansen J-test of overidentifying
restrictions under different regimes are discussed, and a Ljung-Box autocorrelation test in the expectation errors is proposed and computed to test the appropriateness of the polynomial approximation of expectations of nonlinear decision rules.

The plan of the paper is as follows. Section 2 outlines the asymmetric model. In Section 3, the GMM estimation results are given, together with tests on the overidentifying restrictions, stationarity conditions, and model specification tests. In Section 4 we discuss the PEA method for solving dynamic nonlinear Euler equations, we explain the experiment to assess the model's nonlinear performance, and we present the simulation results. Conclusions are drawn in Section 5.

2. A model for asymmetric production factor dynamics

The purpose of the model is to investigate to what extent there are asymmetries in the dynamics of firms' decisions to increase or reduce the stocks of production factors. We assume that firms, when making contingency plans on the use of factor inputs, account for differences in adjustment costs during different phases of the business cycle. Optimal dynamic decision rules for factor input are derived, that have a unique forward looking solution (are continuously differentiable with respect to the decision variables as well as to the model’s parameters).

The objective of firms is to maximize the real present value of expected profits over an infinite time horizon:

$$\mathbb{E} \left\{ \sum_{\tau=0}^{\infty} R_{t,t+\tau} (\text{output}(t+\tau) - \text{variable costs}(t+\tau) - \text{adjustment costs}(t+\tau)) \mid \Omega_t \right\}$$

(2.1)

with respect to the number of workers, the stock of productive capital, and the utilization of labor and capital. In line with Pindyck and Rotemberg (1983) and Shapiro (1986) the discount factor $R_{t,t+\tau}$ is assumed to be variable over time and equal to the inverse of one plus the real interest rate over the period $t$ to $t + \tau$ set at time $t$. $\Omega_t$ is the relevant information set at time $t$.

One particularly convenient form of convex adjustment costs that allows for asymmetry in marginal costs (AAC) and contains the linear-quadratic specification as a special case is a generalized asymmetric cost function (GACF) of net changes in the stocks of production factors (Pfann and Verspagen, 1989):$^5$

$$\text{Adjustment Costs}(t) \equiv \text{AAC}(\Delta K_t) + \text{AAC}(\Delta N_t),$$

(2.2)

$^5$ See Varian (1975) and Zellner (1986) for the comparable LINEX specification. The LINEX model is less general and does not nest the quadratic adjustment costs specification.
where
\begin{align}
\text{AAC}(\Delta K_t) &= \exp(\beta_K \Delta K_t) - 1 - \beta_K \Delta K_t + \frac{1}{2} \gamma_K (\Delta K_t)^2, \\
\text{AAC}(\Delta N_t) &= \exp(\beta_N \Delta N_t) - 1 - \beta_N \Delta N_t + \frac{1}{2} \gamma_N (\Delta N_t)^2
\end{align}
(2.3) (2.4)

with \( K_t \) and \( N_t \) being the stock of capital at the end of period \( t \) and the number of workers at period \( t \), respectively, \( \Delta \) is the first-difference operator, \( \gamma_K \) and \( \gamma_N \) are constant parameters measuring the adjustment costs of net changes and \( \beta_K \) and \( \beta_N \) are constant parameters measuring the marginal asymmetry between positive and negative net changes in factor inputs. Note that if \( \beta_j \), \( j \in \{ K, N \} \), is negative, expansions incur less costs than reductions, having a negative impact on the speed of adjustment during contractions. The set of conditions: \( \gamma_j > 0 \), \( j \in \{ K, N \} \) render \( \text{AAC}(\cdot) \) being strictly convex, such that \( \text{AAC}(0) = 0 \), \( \text{AAC}'(0) = 0 \), and \( \Delta K_t = 0 \) and \( \Delta N_t = 0 \) correspond to a global minimum.

We use net changes in the capital stock which includes the scrapping of capital in Eq. (2.3), because most of the adjustment costs are related to net capital changes. Using gross changes instead would imply adjustment costs being measured in gross investments,\(^6\) \( I_t: \text{AAC}(I_t) \), with \( I_t \) being nonnegative, in which case we would miss all the ongoing disinvestments. The functional form of \( \text{AAC}(\Delta N_t) \) and the fact that we only consider industry-level data do not imply nor require that hiring and firing of workers cannot take place simultaneously. We only assume that an increase or reduction of the absolute size of the workforce induces additional costs of adjustment, and that these costs depend on the sign as well as the magnitude of the change in \( N_t \).

An important mechanism in the asymmetric model is the speed of adjustment at which the stocks of production factors change through time. If adjustment costs are asymmetric, the adjustment speed will, \textit{ceteris paribus}, differ accordingly. Pfann (1996) found \( \beta_K \) and \( \beta_N \) to be both negative for Dutch manufacturing for a more restricted time period up to 1984.IV in a model without an explicitly estimated output equation; Pfann and Palm (1993) found important asymmetries between hiring costs and firing costs for blue and white collar workers in a model for the Dutch industry over the period 1971.1–1984.IV, with the stock of capital not being included in the set of decision variables but considered as predetermined and co-trending. They found adjustment speeds varying substantially, not only among types of workers, but also between different phases of the business cycle. Jaramillo et al. (1993) found strong empirical support for asymmetric adjustment costs for labor using panel data of 52 Italian firms for the period 1958–1988.

\(^6\) As, for instance, in Kennan (1979), Meese (1980), and Pindyck and Rotemberg (1983).
The variable cost in real terms of factor utilization is the sum of investment expenditure and the wage bill:

\[
\text{Variable Costs}(t) = Q_t(K_t - (1 - \delta(U_t))K_{t-1}) + W_tH_tN_t,
\]

where labor costs are the real hourly wage costs, \(W_t\), times the total number of hours worked, \(H_tN_t\), and investment expenditure equals the real price of investment goods, \(Q_t\), times gross investment, with \(U_t\) being the rate of capacity utilization, and where the time-varying rate of capital depreciation, \(\delta(U_{t-1})\) accounts for Keynes' notion of intertemporal substitution possibilities of using up-capital. Capital depreciates faster if it is used more intensively. We assume that the deterioration of the capital stock is linearly related to the rate at which it is being used,\(^7\)

\[
\delta(U_t) = \delta U_t, \quad 0 < \delta < 1.
\]

We assume that hours worked and capacity utilization of the current stock of capital can be changed at zero costs. Hours worked and capacity utilization rates are relevant to determine the current output, but they are state variables for future expectations of the optimal sizes of the workforce and the capital stock. Defining \(CU_t = K_{t-1}U_t\), and \(L_t = N_tH_t\), as the utilized capacity of the productive capital stock and the total production hours, respectively, we assume that output, \(Y_t\), is produced by a Cobb–Douglas technology

\[
\text{Output}(t) = Y_t = A_t(CU_t)^{\alpha_K}(L_t)^{\alpha_N}, \quad 0 \leq \alpha_K, \alpha_N \leq 1,
\]

where \(A_t\) measures the accumulated effect of productivity shocks, generated by the following process:

\[
\log(A_t) = \rho_0 + \rho_1 \log(A_{t-1}) + \varepsilon_t,
\]

with \(\rho_i, i = 0,1\), being constant parameters, and \(\varepsilon_t\) being an i.i.d. productivity shock.

The input scenarios for the capital stock and the workforce are derived from the first-order necessary conditions (FONCs) of the planning problem (2.1) with respect to \(K_t\) and \(N_t\). The FONCs for capital \(K_t\) and labor \(N_t\) are, respectively,

\[
\begin{align*}
\mathbb{E}\{R_{t,t+1}(x_K Y_{t+1}/K_t + Q_{t+1}(1 - \delta U_{t+1}) + \beta_K \exp(\beta_K \Delta K_{t+1}) - \beta_K + \gamma_K \Delta K_{t+1})[\Omega_t] - Q_t - \beta_K \exp(\beta_K \Delta K_t) + \beta_K - \gamma_K \Delta K_t = 0
\end{align*}
\]

\(^7\) Alternative specifications for intertemporal substitution possibilities of using up-capital are given in Taubman and Wilkinson (1970) and Greenwood et al. (1988), and more recently in Burnside and Eichenbaum (1994).
\[ E \{ R_{t+1} | \beta_N (\exp(\beta_N \Delta N_{t+1}) - \beta_N + \gamma_N \Delta N_{t+1}) \} \Omega_t + \alpha_N Y_t / N_t - W_t H_t \]
\[ - \beta_N \exp(\beta_N \Delta N_t) + \beta_N - \gamma_N \Delta N_t = 0. \] (2.9)

The FONCs will be jointly estimated with the production function (2.7a) which after substitution of the process for technology (2.7b) becomes

\[ \log(Y_t) = \rho_0 + \rho_1 \log(Y_{t-1}) + \alpha_k (\log(CU_t) - \rho_1 \log(CU_{t-1})) \]
\[ \quad + \alpha_N (\log(L_t) - \rho_1 \log(L_{t-1})) + e_t. \] (2.10)

The model that we use to investigate the different impacts of the two sources of asymmetry on production factor dynamics relates to the literature on asymmetric costs of adjustment (e.g. Weiss, 1985; Chang and Stefanou, 1988). A model with the built-in possibility of asymmetric input adjustments can potentially generate asymmetric endogenous cycles (e.g. Cassings and Kollintzas, 1991). Interesting features of our model are the fact that the linear-quadratic (LQ) model for factor input is nested in ours; the discount rate varies over time (cf. Pindyck and Rotemberg, 1983; Shapiro, 1986); capacity depreciation varies over time to account for intertemporal substitution of using up-capital (cf. Greenwood et al., 1988); capital adjustments are expressed as net changes and include scrapping of capital, and utilization of production capacity (hours worked), the rate of capacity utilization of capital) is endogenous (Epstein and Denny, 1980) and can be changed costlessly and without delay. As a result of the endogeneity assumption, the utilization rate of capital and the number of hours worked will be instrumented in the estimation. Further refinements of the model along the lines of Prucha and Nadiri (1996) could be implemented at the costs of substantially increasing the complexity of the model and consequently of the model's solution.

3. Estimation of the asymmetric model

In this section we report the results of estimating the asymmetric model for the Netherlands manufacturing sector. We used seasonally adjusted quarterly data for the period 1971.I–1990.IV. Definitions and data sources are given in the appendix. Plots of the marginal productivity of labor and real wage costs and of capital and real investment costs are given in Figs. 1a and b, respectively. Eqs. (2.8)–(2.10) will be estimated simultaneously using generalized methods of moments (GMM). The choice of instrumental variables is given in the data appendix. GMM is robust with respect to skewness or excess kurtosis in the driving variables and yields consistent parameter estimates if the innovations in productivity and future expectations errors are stationary and ergodic. If these conditions are satisfied, and if we detect asymmetry in the FONCs, i.e. if the asymmetry parameters \( \beta_k \) and \( \beta_N \) are found to be significant, this is unlikely to
Fig. 1(a). Marginal labor productivity and real labor costs (Netherlands manufacturing, 1971:1–1990:4).

Fig. 1(b). Marginal capital productivity and real investment costs (Netherlands manufacturing, 1971:1–1990:4).
be due to nonlinearity in the forcing variables. The estimation of the model is
done by the TSP 4.2 using the GMM procedure. We used Andrews' (1991)
method for heteroskedasticity and autocorrelation consistent covariance matrix
estimation.

When we first estimated the model (2.8)–(2.10), the parameters \( \alpha_K \) and \( \alpha_N \) of
the CD production function were estimated unconstrained. We found that the
sum \( \alpha_K + \alpha_N \) was close to unity (\( \alpha_K + \alpha_N = 1.056 \), with \( p \)-value of CRS test equal
to 0.301), while the accumulated shocks resembled a near unit-root with drift
process. The identification problem of constant or increasing returns to scale, on
the one hand, and non-stationary accumulated productivity shocks, on the
other, is a difficult one and beyond the scope of this paper. In conformity with
the macroeconomic literature on factor hoarding that is related to our work (see
Burnside and Eichenbaum, 1994), we assumed a constant returns to scale
production technology, with \( \alpha_K = 1 - \alpha_N \), and did not impose a priori the unit
root in process for \( A_t \). Table 1 presents the GMM-parameter estimates of
\( \Theta = (\alpha_N, \rho_0, \rho_1, \beta_K, \gamma_K, \delta, \beta_N, \gamma_N) \), and specification tests of the asymmetric
model (2.8)–(2.10).

Despite its parsimonious parameterization the model accounts for an
adequate fit to the data. In Fig. 2 residuals are plotted of the production
function (Fig. 2a), and of the FONCs on capital input (Fig. 2b) and labor
demand (Fig. 2c). Not only the residuals of the asymmetric model are shown,
but the residuals from fitting the model with the asymmetry parameters set to
zero (the LQ model) are also included. The motivation for our work, as stated in
the introduction, becomes immediately evident from these figures. Fig. 2a shows
that the fit of the – fundamentally static – production technology does not
change much with the dynamic specification chosen for its factor inputs.
Figs. 2b and c, however, illustrate how the model without asymmetry fails to

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8 The decision variables \( K_t \) and \( N_t \) have unit roots, and we may be estimating two nonlinear
cointegrating relations in (2.8) and (2.9). Without prior knowledge of the number of unit roots in the
model with both stationary and nonstationary components the GMM procedure should be
modified in order to achieve optimality in the estimation (see Kitamura and Phillips, 1994). In the
theoretical model, however, the unit roots are known and the stochastic long run relations can be
derived from Eqs. (2.8) and (2.9). When in the steady state there is no discounting (\( R_{t,t+1} = 1 \) and
\( \Delta K_t = \Delta N_t = 0 \), the Jorgenson condition that marginal product equals marginal costs is
\( 1 - \alpha_N Y_t / K_t - 1 = Q_t \) and \( \alpha_N Y_t / N_t = W_t H_t \) (see also Figs. 1a and b). The parameter \( \alpha_N \) appears in
the production function as well as in the FONCs. The three-equation system is estimated with these
particular cross-equations restrictions. Stationarity is investigated after estimation using the GMM
residuals. Eq. (2.10) is estimated in log-levels while for the FONCs the unit roots were imposed prior
to estimation.

9 Options HETERO and NMA = 1, in the TSP4.2 routine for IV-GMM estimation. The
instrumental variables used for estimation are described in the data appendix. The model is
overidentified.
match peaks and fails to model depths of troughs as well as the model with asymmetry in adjustment costs.

Stationarity is tested by the Sargan–Barghava (1983) statistic (SB) reported in Table 1 and does not point at unit roots in the residuals. The solid lined residuals in Figs. 2a–c, confirm this conclusion. Other statistics given in Table 1 are: the Hansen–Sargan $J$-statistic on overidentifying restrictions of the instrumental variables, asymptotic $t$-ratios for individual parameter significance, and Gallant’s (1987) likelihood-ratio type statistic on the joint restriction of symmetry in adjustment costs $\beta_K = \beta_N = 0$. Given that the estimates of $\gamma_K$ and $\gamma_N$

<table>
<thead>
<tr>
<th>Table 1</th>
<th>GMM estimation results of the asymmetric model* (Netherlands Manufacturing Sector; sample period 1972.I–1990.IV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output ($Y$)</td>
<td>$\rho_0 = 0.007 (5.94)$</td>
</tr>
<tr>
<td>Capital ($K$)</td>
<td>$\beta_K = -26.09 (-6.39)$</td>
</tr>
<tr>
<td>Labor ($N$)</td>
<td>$\delta = 0.012 (9.35)$</td>
</tr>
<tr>
<td><strong>Goodness-of-fit indicators</strong></td>
<td></td>
</tr>
<tr>
<td>Output ($Y$)</td>
<td>0.978</td>
</tr>
<tr>
<td>Capital ($K$)</td>
<td>0.989</td>
</tr>
<tr>
<td>Labor ($N$)</td>
<td>0.982</td>
</tr>
<tr>
<td><strong>Specification tests</strong></td>
<td></td>
</tr>
<tr>
<td>Hansen–Sargan $J$-test</td>
<td>$\chi^2(19) = 15.684 (p$-value $= 0.678)$</td>
</tr>
<tr>
<td>Symmetry ($H_0: \beta_K = \beta_N = 0$)</td>
<td>$\chi^2(2) = 18.684 (p$-value $= 0.000)$</td>
</tr>
</tbody>
</table>

*Asymptotic $t$-ratios are given within parentheses.

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Fig. 2(a). GMM residuals from production function (LYres, 1972.I–1990.IV).
\( \gamma_N \) are both positive, the objective function is concave and we have a global optimum. The test statistics in Table 1 on the importance of the asymmetry relay an unambiguous message: as GMM is robust against departures from symmetry in the multivariate distribution of the expectations errors and productivity shocks, the finding of significant nonlinearity in the propagation mechanism establishes its importance as a source of asymmetry in factor demand. The linear-quadratic \( AC \) model is rejected in favor of the asymmetric \( AC \) model.

The two asymmetry parameters, \( \beta_K \) and \( \beta_N \), are found to be significantly different from zero. An important matter, however, is the robustness of this result: Could the measured asymmetry vanish in a more complicated linear-quadratic functional form of adjustment costs, allowing, for instance, for interrelated cross-terms, or if a more complicated technology model were used?
One could generalize (2.2) by assuming that the adjustment costs AAC also depend on the interactive terms $\Delta K_t, \Delta N_t$. The cost function composed of variable and adjustment costs would then show closer resemblance to generalized cost functions, but extended with asymmetry terms. In related previous work (Pfann, 1996), the coefficients of $\Delta K_t, \Delta N_t$ were found to be insignificantly different from zero. The limited contribution of interrelated terms in the generalized cost or profit functions with internal adjustment costs corroborates similar results found by other authors (cf. Epstein and Yatchew, 1985).

The Cobb–Douglas technology is quite restrictive on the surface, although it is not clear how one would solve the dynamic planning problem with a specification that would be more complicated. In related previous work (Kodde et al., 1990; Palm and Pfann, 1990) we used linear-quadratic technologies with interrelation terms, but we have not used interrelated translog or CES production functions, for example. The reason for this is twofold. First, the linear-quadratic technology allows for - analytical - closed-form solutions of the FONCs if the adjustment costs specification is linear-quadratic as well. This model proved to be too restrictive to describe in an accurate way the dynamics of factor demand. Second, more complicated production technologies are basically adding structure to the statics of the model and not to its dynamics. Together with the above-mentioned facts that dynamic cross-terms in the adjustment costs specification were not found to be very effective, and the often encountered rejection of overidentifying restrictions in models with complicated static technologies and simple - linear-quadratic - dynamic costs structures, we find this ample support for our conjecture that the asymmetry found in adjustment costs is not only theoretically attractive but is also empirically a better extension of the dynamic factor demand model.

The two asymmetry parameters, $\beta_k$ and $\beta_n$, are found to be significantly negative. But, are these parameter values large or are they minor? We can only partially answer this question, because we are not able to compute adjustment speeds directly from this model. What we can do, however, in the light of the extensive literature that marks the importance of the total second order effect of adjustment costs in adjustment speed, is to compute the contribution of behavioral asymmetry to the total second order effects for capital and labor. The total second-order effect measuring the curvature of adjustment costs can be computed as the parameters of the second-order Taylor series expansions of (2.3) and (2.4) evaluated about $\Delta K_t = 0$ and $\Delta N_t = 0$, respectively, given estimates for $\gamma$ and $\beta$. The total second-order effects of adjustment costs are

\[
\Gamma_k \equiv \gamma_k + \beta_k^2 = 1274.39 \quad \text{(S.E. = 380.36)}
\]

and

\[
\Gamma_n \equiv \gamma_n + \beta_n^2 = 395.80 \quad \text{(S.E. = 97.36)}.
\]
We find $\Gamma_K > \Gamma_N > 0$, which is the usual result in this literature. Next, we define the *rate of asymmetry* as follows:

$$r_{AS}(i) = \beta_i^2/(\gamma_i + \beta_i^2), \quad i = K, N.$$  

If $r_{AS}(i) = 0$, asymmetry is of no importance (this hypothesis has been rejected by the symmetry test given in Table 1). If $r_{AS}(i) = 1$, only asymmetry contributes to the (implied) adjustment speed. We find $r_{AS}(K) = 0.53$ (S.E. = 0.09), and $r_{AS}(N) = 0.48$ (S.E. = 0.03). We therefore conclude that 53% of the total second-order effect of adjustment costs to the speed of adjustment for capital and 48% for labor is due to *behavioral asymmetry*.

For capital this means that the building up of new capital during expansions is less costly and consequently realized faster than the scrapping of capital during recessions. Much scrapping occurs by means of plant-closing which in Netherlands is bound by institutional regulations that constitute major hurdles. Firms refrain from scrapping during recessions, while they initiate new investment projects fast in times of high expectations on the profitable yields of capital assets. For labor it means that workforce expansions are less costly than contractions. These differences arise from labor market legislation, labor market tightness, union power, the composition of the aggregate workforce, and differences between net and gross costs of workforce changes (Hamermesh and Pfann, 1996b). Our results confirm earlier findings on asymmetric dynamics in industry models of factor demand, but appear to be in contradiction with Jan Tinbergen’s quotation at the beginning of this paper.

4. **Solving and simulating the asymmetric model**

The asymmetric factor adjustment model consists of the three equations that together with the assumption of rational expectations and the process of the driving forces describe the solution of the stochastic optimization problem (2.1) in an implicit way. The factor input decisions depend on *external* nonlinear random processes for the driving variables (the real factor prices and the productivity shocks) and on *behavioral* asymmetry that is captured by the asymmetry in adjustment costs. When using GMM, behavioral asymmetry was found to be significant in manufacturing data for Netherlands. In order to know to what extent each of these potential sources contributes to the asymmetry in factor input cycles the model will be simulated. In this model any non-linearity in factor prices affects factor inputs, but not vice versa. Note, however, that things would be even more complicated in an equilibrium model with endogenous prices, where the nonlinearity in factor prices could itself be generated by the asymmetry in adjustment costs.
4.1. Solving the model by PEA

Analytical solutions of stochastic factor input models with unobserved rational expectations and nonlinear adjustment mechanisms, like our model, are not available in general. A number of numerical solution strategies have been proposed in the literature (cf. Taylor and Uhlig, 1990). Many of these numerical algorithms are reasonably accurate. Recently, Christiano and Fisher (1994) ran a race among six of the methods mostly used and showed that on the basis of speed, accuracy, and convenience of implementation, the parameterized expectations algorithm (PEA) introduced by Den Haan and Marcet (1990) dominates the others. In this paper, we will use the PEA method to approximate the equilibrium decision rules for capital and labor as solutions of the asymmetric factor demand model described and estimated in the previous sections.

Den Haan and Marcet (1990) describe the working of the PEA method for the single-equation nonlinear stochastic growth model and Marcet and Marshall (1994) for a multi-equations model. We extend and implement the PEA technique to solve two first-order necessary conditions with cross equation restrictions simultaneously. We shall introduce some simplifying assumptions that facilitate the numerical solution for the equilibrium, but still allows us to unravel the two potential sources of external nonlinearity and behavioral asymmetry. More specifically, we shall approximate expectations by a quadratic polynomial of a subset of the state variables at time $t$.

The decision variables in the model that determine the cycle (the endogenous variables) are $Y$, $K$ and $N$. Other variables in the model are procyclical, either because in this model they are assumed to be exogenous or because they are assumed to be flexible input variables. In the following the discount rate, $R$, and the utilization of factor inputs, $U$, and $H$, are held constant through time and equal to their respective sample means, $\bar{R}$, $\bar{U}$, and $\bar{H}$. The predetermined variables in our model, the variables for which we have not put forward a structural model, are the vector of real input prices, $P_i = (Q_i, W_i)'$ and productivity shocks $\varepsilon_t$. We shall assume laws of motions for the predetermined variables. The nonlinear adjustment model for factor inputs consists of three equations: eq. (2.10) for output, and the two FONCs, (2.8) and (2.9), for capital.

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10 An alternative strategy would be to derive and estimate demand equations for $U$ and $H$, and simultaneously solve the model for $Y$, $K$, $N$, $U$, and $H$. Because we can find consistent estimates for the asymmetry parameters by applying GMM without using the FONCs for $U$ and $H$, we make the simplifying assumption that $U$ and $H$ are time-invariant and equal to their sample means. This facilitates the numerical derivation of the reduced demand equations for $K$ and $N$ in a major sense, without losing the possibility to investigate the impact real factor input prices have on the asymmetric cycles for $K$ and $N$. 
and labor. After substitution of $\tilde{R}$, $\tilde{U}$ and $\tilde{H}$ for $R_t$, $U_t$ and $H_t$, we rewrite the FONCs for capital $K_t$ and for $N_t$ as follows:

$$E\{g_1(K_{t+1}, Y_{t+1})|\Omega_t\} + E\{Q_{t+1}(1-\delta\tilde{U})|\Omega_t\} - \beta_K \tilde{R}^{-1} (\bar{Q}_t + \beta_K \exp(\beta_K \Delta K_t) - \beta_K + \gamma_K \Delta K_t) = 0$$

(4.1)

and

$$E\{g_2(N_{t+1})|\Omega_t\} - \beta_N - \tilde{R}^{-1} (\bar{W}_t H + \beta_N \exp(\beta_N \Delta N_t)) - \beta_N + \gamma_N \Delta N_t - \alpha N Y_t/N_t = 0,$$

(4.2)

where

$$g_1(K_{t+1}, Y_{t+1}) \equiv (1-\alpha_N)Y_{t+1}/K_t + \beta_K \exp(\beta_K \Delta K_{t+1}) + \gamma_K \Delta K_{t+1}$$

and

$$g_2(N_{t+1}) \equiv \beta_N \exp(\beta_N \Delta N_{t+1}) + \gamma_N \Delta N_{t+1},$$

define the nonlinear functions of the future decision variables for which the conditional expectations have to be determined by solving the model.

Given a law of motion for $P_i = (Q_i, W_i)'$, the conditional expectation of $Q_{t+1}$ in (4.1) is known. Eq. (2.10) determines the relationship between $Y$ and $K$ and $N$. We will use (2.10) accordingly in the subsequent analysis. In the sequel, we will assume that the conditional expectations of $g_1(K_{t+1}, Y_{t+1})$ and of $g_2(N_{t+1})$ being nonlinear functions of unknown form of the state variables at time $t$ can be approximated by polynomial functions

$$P_i(Z_t, \zeta^i_t), \quad i = K, N,$$

(4.3)

of degree $n$ in the vector $Z_t$, and $\zeta^i_t$ is a set of $m$ constant parameters. The vector $Z_t$, which is a subset of all relevant state variables in $\Omega_t$ is given by $Z_t = (Y_{t-1}, K_{t-1}, Q_{t-1}, N_{t-1}, W_{t-1})'$. The polynomials in (4.3) refer to Weierstrass' approximation theorem for continuously differentiable functions on compact mappings of the state space of finite dimension $q$, $\mathbb{R}^q$, into $\mathbb{R}$ by letting $n \to \infty$.

With this set of polynomial functions $P_i(\cdot, \cdot)$, we shall approximate the equilibrium demand equations for $K$ and $N$ (cf. Marcet and Marshall, 1994). The accuracy of the simulated solutions for $K_t$, $N_t$ and $Y_t$ depends on the choice of $n$, the order of $P_i$. Den Haan and Marcet (1994) showed that fairly accurate results were obtained for $n > 1$. We choose $n = 2$. Given the dimension $m$ of each $\zeta^i_t$, $n$ higher than two would require a very large sample size $T$ of the simulations to guarantee satisfactory estimation results for $\zeta$. Christiano and Fisher (1994) suggested the use of Legendre polynomials with orthogonal elements could reduce the problem of multicollinearity. That problem arises when $n$ becomes large, i.e. larger than 2. For $n = 2$, the polynomials $P_2(Z_t, \zeta^i_t)$ have an intercept,
5 linear and 5 quadratic terms, and 10 cross-product elements of $Z_t$, so that $m=21$. The coefficients of these terms are elements of the $(21 \times 1)$ vector $\zeta_i$.

The PEA method is designed to calculate fixed points $\zeta^i_K$ and $\zeta^i_N$ such that

$$P_2(Z_i; \zeta^i_K) = R^{-1}(Q_i + \beta_K \exp(\beta_K \Delta K_i) - \beta_K + \gamma_K \Delta K_i) + \beta_K - E\{Q_{t+1}(1 - \delta U) | \Omega_i\} \quad \forall t,$$

and

$$P_2(Z_i; \zeta^i_N) = R^{-1}(W_i \bar{H} + \beta_N \exp(\beta_N \Delta N_i) - \beta_N + \gamma_N \Delta N_i) - \alpha_N Y_i / N_i + \beta_N \quad \forall t,$$

evaluated at the given estimates for the structural parameters in $\Theta$.

Following Marcet and Marshall (1994), we define $S^i: \Re^m \rightarrow \Re^m$, as

$$S^K(\zeta) = \arg \min_{\zeta^i_K} T^{-1} \sum_{t=0}^{T} \|g_1(K_{t+1}(\zeta), Y_{t+1}(\zeta)) - P_2(Z_i(\zeta); \zeta^i_K)\|^2$$

and

$$S^N(\zeta) = \arg \min_{\zeta^i_N} T^{-1} \sum_{t=0}^{T} \|g_2(N_{t+1}(\zeta)) - P_2(Z_i(\zeta); \zeta^i_N)\|^2,$$

where $g_1$, $g_2$, and $Z_i$ are evaluated at $\zeta=(\zeta^i_K; \zeta^i_N)$, $\zeta_i$, $i = K, N$, which are the parameters of the polynomials from the previous iteration; and $g_1(K_{t+1}(\zeta), Y_{t+1}(\zeta))$ and $g_2(N_{t+1}(\zeta))$ are the values at time $t+1$ and $t$ of the nonlinear functions of $Y_{t+1}(\zeta)$, $K_{t+1}(\zeta)$, $N_{t+1}(\zeta)$, $K_i(\zeta)$ and $N_i(\zeta)$ as being obtained by solving the nonlinear system (4.1), (4.2) and (2.10) based on expectations parameterized with $\xi$. This process is repeated until parameters $\zeta^i=(\zeta^i_K; \zeta^i_N)$ are found that satisfy the fixed point problem

$$\zeta^i = S^i(\zeta^i), \quad i = K, N.$$

The iteration procedure to obtain the fixed point $\zeta^i$ can be interpreted as a discrete-time least-squares learning process during the decision period $t$ (cf. Marcet and Sargent, 1989). The consecutive steps of the iteration procedure are as follows.

The first step is to generate series of length $\tau$ for the real factor prices $P_t$, and for the i.i.d. productivity shocks $\varepsilon^Y$. Those series are drawn one time only for every replication of series for $K$, $N$, and $Y$ of length $\tau$.

In the second step we choose starting values for the $m$-vectors $\zeta^0_K$ and $\zeta^0_N$ using OLS to estimate $\zeta^*$ in (4.5) and (4.6) on the actual data, and calculate initial values for the expectations

$$E\{g_1(K_{t+1}, Y_{t+1}) | \Omega_i\} = P_2(Z_i; \zeta^0_K), \quad (4.8a)$$
and
\[ E\{g_2(N_{t-1}) \mid \Omega_t \} = P_2(Z_t; \xi^0_N). \]  
(4.8b)

We substitute the values for the expectations in (4.8a) and (4.8b) into (4.1) and (4.2) and apply Newton's method for finding the iterative solutions for \( Y_t(\xi), K_t(\xi), \text{and} \ N_t(\xi), t = 1, \ldots, T, \) using the system (4.1), (4.2) and (2.10), which is well defined since the Hessian with respect to \( Y, K \) and \( N \) is not singular (cf. Bazarraa, et al., 1993, Chapter 8). The system is then solved using a nonlinear equation solver that uses second-order necessary conditions for \( K \) and \( N \). Convergence results in simulated series for \( K, N, \) and \( Y \) of length \( \tau \). For the starting values \( K_0, N_0, \) and \( Y_0 \) we use the actual observations of 1971.I.

The third step is to update \( \xi \). In order to obtain \( \xi^{j+1}, j = 1, 2, \ldots, \), being the vector \( \xi \) of the \( j \)th iteration, we run the least-squares regressions (4.3) and (4.6) simultaneously. Let \( \xi^{j} \) be the \( j \)th iteration's value of \( \xi \) and let \( S(\xi^{j}) \) be the new solution. To obtain a new estimate for \( \xi^{j+1} \) we use a Levenberg-Marquardt type method, and compute the following algorithmic scheme:
\[ \xi^{j+1} = (1 - \lambda) \xi^{j} + \lambda S(\xi^{j}), \quad 0 < \lambda \leq 1, \]  
(4.9)

where \( \lambda \) is a damping factor to prevent overshooting the minimum of the sum-of-squared-errors function. One chooses \( \lambda = 1 \) if the system is simple and not explosive, and a value \( \lambda < 1 \) otherwise. This process is repeated until
\[ \left| \frac{\xi^{j+1} - \xi^{j}}{\xi^{j}} \right| < \xi, \]  
(4.10)

where \( \xi \) is an arbitrarily small number that determines the precision of the approximate future expectations and in part also the computational duration.

4.2. Simulation of the asymmetric model

We investigate the impact of external nonlinearity on asymmetric cyclicality of factor input dynamics by means of the PEA method. Model-based parameter estimates of asymmetry for capital and labor are simulated under two different laws of motion for the real price of investment and real wage costs: a bivariate linear ARI(1,1) process and a bivariate nonlinear NARI(1,1) process. The impact of external nonlinearity on the statistical properties of the estimates of the internal asymmetry parameters is then analyzed.

When \( \xi^{j} \) is obtained, the pseudodata for \( Y, K, N, Q, \) and \( W \) of length \( \tau \) from the asymmetric adjustment model are obtained and will be stored in \( X_{\tau} \). Repeating the PEA algorithm \( R \) times produces \( R \) different \((\tau \times 5)\) matrices \( X_{\tau} \) with pseudodata, from which the simulated distribution for the GMM estimates of the structural parameters of the Euler equations \( \beta_K, \beta_N, \gamma_K, \gamma_N \) and \( \delta_K \) will be derived.
When simulating the model, the productivity shocks are drawn from a
symmetric normal distribution with constant standard deviation, \( \tilde{\sigma}_t^2 = 0.01626 \)
taken from the previous section as the estimate for \( \rho \). Moreover, we will impose
two different generating mechanisms of real factor prices, \( P_t = (Q_t, W_t) \), for the
simulations. One has several options to choose from when to decide which
nonlinear process for \( P_t \) is appropriate. Various nonlinear multivariate auto-
regressive models are discussed in Granger and Teräsvirta (1993). Their
transition functions (e.g. exponential AR, smooth transition AR) are often
characterized by a set of transition parameters \( \Gamma \). Using standard nonlinear
optimization routines (Newton–Raphson, Gauss, conjugate gradient method),
it is known that \( \Gamma \) is very hard to estimate together with the AR coefficients.
We therefore assume a bivariate second-order polynomial AR model as the
nonlinear law of motion for \( P_t \). Such a polynomial can always be regarded as
a Taylor-series approximation of a more general nonlinear process. The
bivariate nonlinear AR(1,1) process we will use yields

\[
\Delta P_t = \pi^N + \Pi_1^N \Delta P_{t-1} + \Pi_2^N (\Delta P_{t-1})^2 + \epsilon_t^N \sim N(0, \Sigma_N^N),
\]

(4.11)

where \( \pi^N \) is a \((2 \times 1)\)-vector, \((\Delta P_{t-1})^2 = ((\Delta Q_{t-1}^2), (\Delta W_{t-1}^2)) \) and \( \Pi_1^N \) and \( \Pi_2^N \) are
\((2 \times 2)\) matrices with constant parameters.

A bivariate linear AR(1,1) process of \( P_t \) yields

\[
\Delta P_t = \pi^S + \Pi^S \Delta P_{t-1} + \epsilon_t^S \sim N(0, \Sigma_P^S),
\]

(4.12)

where \( \pi^S \) is a \((2 \times 1)\)-vector and \( \Pi^S \) is a \((2 \times 2)\) matrix with constant parameters.
The estimates of the unknown coefficients of Models I and II are given in
Table 2.

From Table 2 it is difficult to decide whether nonlinearity matters for the
series of real factor prices. The individual parameter estimates for the matrix \( \Pi_2^N \)
are only marginally significant for \( W_t \). An overall LR-test on nonlinearity (\( H_0 : \Pi_2^N = 0 \)) does not favor nonlinearity.

For the PEA algorithm to converge we chose \( \xi = 0.05 \) and \( \lambda = \frac{1}{2} \). The length of
the simulated series is \( \tau = 76 \) (1972.I–1990.IV); the structural parameters are set
equal to the estimates reported in Table 1; 50 initial periods assure indepen-
dence of initial conditions. The number of runs equals 250. Figs. 3–5 show the
simulated frequency distributions of the GMM estimates of the asymmetry
coefficients \( \beta_k \) and \( \beta_n \), of their asymptotic \( t \)-values and of the Hansen–Sargan
\( J \)-test for overidentification respectively, for those GMM regressions that
converged (232, 233 out of 250). Each of the Figs. 3, 4, and 5 consists of three
panels. The upper panel I refers to the experiments generated with asymmetric
adjustment costs and the nonlinear data generating process for real factor
prices \( P_t \) (4.11). The middle panel II refers to the experiments generated with
asymmetric adjustment costs and the linear data generating process for real
Table 2
Laws of motion for real factor prices* (Netherlands manufacturing sector; sample period 1972.I–1990.IV, $P_t = (Q_t, W_t)$)

<table>
<thead>
<tr>
<th>Model I</th>
<th>$\Delta P_t = \pi^N + \Pi^2_t \Delta P_{t-1} + \Pi^2_t (\Delta P_{t-1})^2 + \epsilon_t^N$ with $\epsilon_t^N \sim N(0, \Sigma^N_t)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi^N$</td>
<td>$\begin{bmatrix} -0.0013 &amp; (0.888) \ 0.1742 &amp; (2.967) \end{bmatrix}$</td>
</tr>
<tr>
<td>$\Pi^N_1$</td>
<td>$\begin{bmatrix} 0.3626 &amp; (2.407) \ 16.1198 &amp; (3.053) \end{bmatrix}$</td>
</tr>
<tr>
<td>$\Pi^N_2$</td>
<td>$\begin{bmatrix} 3.2062 &amp; (0.797) \ 233.725 &amp; (1.651) \end{bmatrix}$</td>
</tr>
<tr>
<td>$\Sigma^N_t$</td>
<td>$\begin{bmatrix} 0.0001 &amp; 0.0034 \ 0.0034 &amp; 0.1725 \end{bmatrix}$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model II</th>
<th>$\Delta P_t = \pi^S + \Pi^2_t \Delta P_{t-1} + \epsilon_t^S$ with $\epsilon_t^S \sim N(0, \Sigma^S_t)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi^S$</td>
<td>$\begin{bmatrix} -0.0007 &amp; (0.467) \ 0.1598 &amp; (2.859) \end{bmatrix}$</td>
</tr>
<tr>
<td>$\Pi^S_1$</td>
<td>$\begin{bmatrix} 0.3975 &amp; (2.701) \ 15.1530 &amp; (2.943) \end{bmatrix}$</td>
</tr>
<tr>
<td>$\Pi^S_2$</td>
<td>$\begin{bmatrix} 0.0001 &amp; 0.0034 \ 0.0034 &amp; 0.1798 \end{bmatrix}$</td>
</tr>
</tbody>
</table>

Specification tests
Linear vs. nonlinear $\chi^2(4) = 6.974$ (p-value = 0.137)

* Asymptotic t-ratios are given within parentheses.

Factor prices $P_t$ (4.12). The lower panel III refers to experiments with symmetric adjustment costs ($\beta_K = \beta_N = 0$) and the linear data generating process for $P_t$ (4.12).

Fig. 3a presents the frequency distributions of the asymmetry parameters $\beta_K$ and Fig. 3b of $\beta_N$ estimated by GMM using the artificial data from three different models. The differences between the upper two panels I and II unveil the (dynamic) effect of a nonlinear process for the forcing variables (external nonlinearity) on the estimates of $\beta$ (internal asymmetry). The median values of $\beta_K$ are all biased upward, with the median value of panel I closest to the true value of $\beta_K = -26.09$, suggesting a nonlinear pricing rule for $Q$ and asymmetric adjustment costs to coexist. The frequency distribution of the simulation estimates of $\beta_K$ appears to be bimodal with the highest mode being close to the true parameter value (upper and middle panels I and II of Fig. 3a); for the true parameter value $\beta_K = 0$, the distribution is unimodal (lower panel III of Fig. 3a). In all three simulation experiments, the distribution exhibits skewness and has a wide range. This indicates that care must be taken when using GMM to estimate the asymmetry parameter of the adjustment cost for capital.
The finite sample distributions of the simulation estimates of $\beta_N$ are unimodal (Fig. 3b). Their range is much smaller than for capital. The distribution appears to be roughly concentrated about the true value of $\beta_N$. In the presence of a nonlinearity in the process for prices (Fig. 3b; upper panel I) the finite sample distribution of $\beta_N$ is approximately symmetric and more concentrated than in
the case of a linear price process (Fig. 3b; middle and lower panels I and II). The existence of external nonlinearity leads to an improvement of the statistical properties of the GMM estimator of the internal asymmetry parameter. Its shape resembles that of an asymptotic Normal distribution better than that for the experiments with linear pricing rules.
As a by-product we are able to investigate the sensitivity in finite samples of GMM estimates for assessing the internal asymmetry in nonlinear factor demand in relation to the possible presence of external nonlinearity. We refer to Prucha and Nadiri (1986) and Tauchen (1986) for early studies of the small sample properties of estimation techniques for dynamic factor demand systems and for GMM by simulation, respectively. The finite sample distributions of the asymptotic t-values (Figs. 4a and b) are skewed for capital and approximately symmetric for labor except for the experiments where symmetry is assumed and asymmetry is estimated (lower panel of Fig. 4b) which distribution is also skewed to the right. Contrary to Nadiri and Prucha (1986) results of the small sample properties of the 3SLS estimator for linear dynamic factor demand systems, we find that the finite sample distributions of functions of the first and second moments of the GMM estimator (mean and t-ratios) exhibit a moderate bias for the asymmetry parameter of capital but almost no bias for that of labor.

Interpreting these results, we conclude that behavioral asymmetry, that arises from asymmetric adjustment costs, substantially contributes to the nonlinearity of factor input dynamics, while external nonlinearity caused by nonlinear processes of forcing variables is of lesser importance. The wide spread of the simulation estimates is very probably caused by the difficulty of finding the nonlinear solutions of the first order necessary conditions for factor inputs. Small shocks can give rise to large fluctuations due to the nonlinearity in the propagation mechanism (adjustment costs and depreciation of the capital stock). This explains the wider range of the simulated asymmetry for capital adjustment costs.

The analysis of the finite sample distributions of means and t-ratios of the GMM estimator can also be considered as alternative model specifications tests. Then the dynamics of labor input are best modeled using an internal asymmetric propagation mechanism and a nonlinear data generating process for the real wage costs (Fig. 4b, panel I). This confirms earlier findings for the Dutch manufacturing sector that firing costs exceed hiring costs and that wage costs do not fall as quickly as they rise. Revealing the best dynamic specification for capital input is less clear-cut. When we base our judgement on the simulation results and relate these to the test statistics reported in Tables 1 and 2 we conclude that from the alternative models that we consider in this paper probably the best choice to describe capital input dynamics is to use an internal asymmetric propagation mechanism and a linear data generating process for the real costs of investments (Fig. 4a, panel II).

Fig. 5 presents the finite sample distributions of the Hansen-Sargan J-test of overidentifying restrictions (orthogonality conditions). The test statistic is based on simulation estimates for the parameters $\beta_k$, $\beta_n$, $\gamma_k$, and $\gamma_n$ in the Euler equations (2.8) and (2.9) holding the parameters of the production function $\rho_0$, $\rho_1$, and $\alpha_n$ fixed at their true values. For each Euler equation, 6 instrumental variables are used: a constant term, the simulated values for $\Delta Y_t-3$, $\Delta K_t-3$, and
Fig. 4(a). Simulated t-distribution of GMM asymmetry coefficient.

\[ \Delta N_{1-3}, \Delta Q_{1-3}, \text{and} \Delta W_{1-3} \] from Model I (4.11) or from Model II (4.12). With six IVs used to estimate five parameters in two equations, the number of overidentifying restrictions (i.e. the number of degrees of freedom of the asymptotic Chi-squared distribution) equals 7. The nonrejection frequencies using a large sample \( \chi^2(7) \) test are 0.9914 (I), 1.0 (II), 0.9784 (III), respectively, if the nominal size is 1%; for a nominal size of 5% they are 0.957 (I), 0.974 (II), 0.828
Fig. 4(b). Simulated t-distribution of GMM asymmetry coefficient.

Panel I: For model with asymmetric adjustment costs and nonlinear factor price process.

Panel II: For model with asymmetric adjustment costs and linear price process.

Panel III: For model with quadratic adjustment costs and linear price process.

For a 10% nominal size we find 0.897(I), 0.909 (II), and 0.672 (III). The rejection frequencies are remarkably close to the nominal sizes except for the linear-quadratic model for which the overidentifying restrictions are rejected too frequently, which is a well-known empirical finding in the literature. Our findings are at variance with the results by Tauchen (1986) who in a different
Fig. 5. Simulated distribution of J-test on overidentifying restrictions.

setup concluded that, if anything, the J-test is biased towards acceptance of the null hypothesis.

Finally, in order to check the appropriateness of the polynomial approximation for the expectations in the Euler equations, we investigate the autocorrelation
of the expectational errors. In the absence of any approximation error in the PEA algorithm, the expectational errors are innovations and therefore have zero serial correlations. In Fig. 6, we present the frequency distributions of the Ljung–Box test of first-order autocorrelation. The Ljung–Box statistic is computed as $TR^2$ where $T$ denotes the sample size and $R^2$ is the squared correlation

**PANEL I**: For model with asymmetric adjustment costs and nonlinear factor price process.

**PANEL II**: For model with asymmetric adjustment costs and linear price process.

**PANEL III**: For model with quadratic adjustment costs and linear price process.

Fig. 6(a). First-order autocorrelation test in one-step-ahead expectation errors.
coefficient associated with a first-order autoregression for expectational errors. Notice that the expectations are based on the fixed point values of $\zeta^e_k$ and $\zeta^e_N$, and that the expectational errors are the residuals of the regressions (4.5) and (4.6) evaluated at $\zeta^e_k$ and $\zeta^e_N$. Panels I, II, and III of Fig. 6 exhibit strong, but stationary, first-order autocorrelation in the expectational errors. Non-rejection
frequencies associated with a large sample $\chi^2$ test and a size of 1% are 0.232 (I), 0.198 (II), 0.302 (III) for $K$ and 0.429 (I), 0.431 (II), and 0.306 (III) for $N$, respectively. The presence of autocorrelation in these errors could be remediated by extending the set of variables to be included in $Z$, in the PEA algorithm, by increasing the degree of the polynomial, and/or by allowing for time-varying parameters $\zeta_t$ of the polynomial. Because, in theory all relevant available information is included in the conditional expectation, one could include lagged values of endogenous and exogenous variables in $Z$. This strategy, however, can easily lead to multicollinearity in the elements of the polynomial. Chebychev polynomials as a basis function have the convenient property of discrete orthogonality, and can therefore be expected to facilitate the computations when the polynomial degree is high (Christiano and Fisher, 1994). Our findings illustrate that the PEA algorithm can be subject to significant approximation errors. We suggest the Ljung–Box test to investigate the appropriateness of the polynomial approximation of expectations of nonlinear decision rules as an alternative to the tests proposed by Den Haan and Marcet (1994).

5. Conclusions

In this paper we investigated the impact of two possible sources of asymmetry on production factor dynamics. One source that we considered is behavioral or internal asymmetry (asymmetry in the propagation mechanism) and results from adjustment costs of changing the input of quasi-fixed production factors. The second source is external nonlinearity that is induced by the variables that drive the model. External nonlinearity could, for example, be due to nonlinear pricing rules, such as downward rigidities, or to asymmetrically distributed random shocks. The difference between those two possible sources is relevant because the first, behavioral, source is partly endogenous and can be controlled by the firm or by institutional changes, whereas the second, external, source is beyond the control of the private and possibly of the public decision makers.11

Based on quarterly data over the period 1971.I–1990.IV of the Netherlands manufacturing sector, we found that asymmetry in the net costs of changing factor inputs (behavioral asymmetry) is the most important source of cyclical

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11 A third possible source is suggested by Caballero and Engel (1993), who showed that idiosyncratic shocks and symmetric costs of adjustment may generate cyclical asymmetries because negative aggregate shocks could trigger more redundancy compared to increases of factor stocks triggered by positive aggregate shocks of a similar magnitude. In this paper we cannot test this hypothesis since our analysis is at an aggregate level.
asymmetry of factor input dynamics. It accounts for about 50% of the total second-order effect of adjustment costs to the (implied) speed of adjustment. Nonlinear processes of real factor prices (external nonlinearity) play a moderate role in explaining the asymmetry phenomenon of factor dynamics. This conclusion suggests that private firms' decision makers and institutional policy makers do have the option to cushion the nonlinearities that occur in factor input dynamics when being regarded as undesirable.

Opposite to the Nadiri and Prucha (1986) findings of the small sample properties of the 3SLS estimator for linear dynamic factor demand systems, we find that the finite sample distributions of functions of the first and second moments of the GMM estimator (mean and t-ratios) exhibit a moderate bias for the asymmetry parameter of capital but almost no bias for that of labor. In samples of about 80 observations, the Hansen–Sargan J-test is found to reject the null of overidentification as frequently as can be expected on the basis of a nominal size of 1, 5 or 10%. This finding is at variance with Tauchen (1986) about the finite sample properties of the J-test based on GMM. A Ljung–Box autocorrelation test in the expectation errors has been suggested for testing the appropriateness of the polynomial approximation of expectations of nonlinear decision rules as an alternative to the tests proposed by Den Haan and Marcet (1994).

Our results confirm earlier findings for the Dutch manufacturing sector that firing costs exceed hiring costs and that wage costs do not fall as quickly as they rise. To indicate what is the most relevant dynamic specification for capital is less obvious. Among the different models that we consider in this paper probably the best is an internal asymmetric propagation mechanism and a linear data generating process for the real costs of investments (Fig. 4a, panel II). We find that firms refrain from scrapping during recessions, while they initiate new investment projects fast in times of high expectations on the profitable yields of capital assets. Most scrapping occurs by means of plant-closing which in Netherlands is bound by institutional regulations that constitute major hurdles. Workforce decreases are costlier than expansions, which may arise from labor market legislation, labor market tightness, union power, the composition of the aggregate workforce, and differences between net and gross costs of workforce changes. However, no structural model for factor prices has been suggested here, so that care must be taken in the wording of the nonlinearity of pricing rules in economic terms. Investigation of an extended version of the model that includes a structural pricing mechanism for production factors would constitute an interesting enhancement of the analysis.

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12 Abel and Eberly (1994) consider lumpy and piecewise linear costs as well, viewing the lumpy costs as idiosyncratic and the linear costs as those of buying and selling uninstalled capital.
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Appendix. Description and sources of quarterly manufacturing data in the Netherlands.

The base year of all prices and indices is 1980.

\( Y \) a seasonally adjusted quantity index of a quarterly average of daily industrial production (National Accounts, Central Bureau of Statistics CBS, The Netherlands)

\( P_y \) producer price index of domestically sold production (Dutch Standard Industrial Classification SBI; SBI 2/3 is the Manufacturing Sector)

\( K \) manufacturing sector (SBI 2/3) capital stock in constant 1980 prices. Annual data provided by the Central Planning Bureau; quarterly fluctuations resemble quarterly fluctuations of manufacturing net investment in fixed assets (Quarterly Accounts, CBS, The Netherlands)

\( U \) rate of capacity utilization (SBI 2/3)

\( UC \) \( ( = K \times U ) \)

\( P_k \) producers price index of domestically placed investment goods (Afzet Binnenland van de Industrie, SBI 2/3)

\( Q \) \( ( = P_k / P_y ) \)

\( N \) is employment of 16–64 yr old working at least 20 h per week (SBI 2/3)

\( H \) average paid working time including overtime of all employees between 16 and 64 yr old (SBI 2/3)

\( L \) \( ( = N \times H ) \)

\( Pl \) costs of labor in current prices per hour worked (SBI 2/3). Since the fourth quarter of 1986, this series is the quarterly updated wage cost. For the period previous to 1986.IV, this series is based on six months data on labor costs and quarterly percentage increases of wages per hour worked (SBI 2/3)

\( W \) \( ( = Pl / P_y ) \)

\( LIS \) labor share of income (SBI 2/3) obtained from quarterly data in Algemene Industrie Statistiek en De Statistiek Werkzame Personen
\( R \) \hspace{1em} \text{real discount rate}

\( \Delta Q_t = (P_t^* Y_t)/(P_t^* L_t) \)

The following variables were used as instrumental variables:

\( \{ \text{Constant}, \Delta Y_{t-3}, \Delta Q_{t-4}, \text{LIR}_{t-4}, \text{SIR}_{t-4}, \Delta UC_{t-3}, \Delta W_{t-3}, \Delta Q_{t-3} \} \),

where LIR is the real yield of long-term government bonds that has been used to compute \( R \), and SIR is the real rate on three months loans to local authorities.

References


