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A dynamic heterogeneous labour demand model for German manufacturing

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This study presents an application of the Generalized Error Correction Model (GECM) for heterogeneous factor demands based on the quadratic cost function. Using data for 26 West German manufacturing industries over the period 1976–1995, it turns out that less general specifications such as the partial adjustment and the static AR(1) model are rejected. Furthermore, both short-run and long-run labour demands of different skill classes are inelastic. Unskilled labour is found to have a somewhat higher wage elasticity in absolute terms than medium-skilled labour. A small part of the shift in demand away from unskilled labour can be explained by the substitutability relationship between intermediate materials and unskilled labour. Between 6 and 13 percent of the observed shift towards high-skilled labour can be explained by capital accumulation.

I. INTRODUCTION

While there is a fairly widespread view that technological change is an important factor explaining the shift in demand away from unskilled labour, other factors such as increasing trade and outsourcing practices are also seen as contributing to the decline of the relative position of unskilled workers (Aghion *et al*, 1999). Most studies on heterogeneous labour demands are, however, based on static models assuming that heterogeneous labour demands adjust to changes in prices instantaneously.

A novelty of this study is that the flexible normalized quadratic demand system proposed by Diewert and Wales (1987) is combined with a general dynamic adjustment process of each input factor. In particular, we apply the Generalized Error Correction Model (GECM) proposed by Anderson and Blundell (1982) is applied to the analysis of the demand for heterogeneous labour.[1] To our knowledge, this paper presents the first application of the GECM based on quadratic factor demands. As noted by Anderson and Blundell (1982), the advantage of the GECM is that it nests a variety of dynamic specifications, such as the partial ECM, the partial adjustment model or the static model with or without a first-order autoregressive error term. In the long-run the static equilibrium model is assumed to hold, whereas in the short-run, the existence of adjustment costs may lead to a delay in the adjustment of factors to changes in output and prices. The dynamic specification of the quadratic factor demands allows us to identify all the relevant determinants of factor demand as well as to distinguish between short and long-run impacts.

The aim of the paper is to investigate possible determinants of heterogeneous labour demand: the price sensitivity of labour by different skill classes and the impact of both materials and capital on the different types of labour. Three skill categories are defined on the basis of the highest formal educational qualification received: (i) workers without any formal vocational certificate; (ii) workers with a certificate of the dual vocational training system; and finally, (iii) workers with a university or technical university degree. The inclusion of materials allows not only the avoidance of the specification bias, but also the study of the

[1] See Allen and Urga (1999) for a recent application of a general dynamic factor demand system derived from a dynamic translog cost function.

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substitution pattern between unskilled workers and materials. Materials (as defined by the German Statistical Office) include imports, services and subcontracting which indirectly reflects a sector's potential to delocalize parts of its production. The GECM is estimated for a four-factor demand system using annual industry data on 26 manufacturing industries for the period from 1976 to 1995.

The disaggregation of labour in different skill classes has been of major interest in applied labour demand analysis for many countries in recent years. Bergström and Panas (1992) as well as Betts (1997) use a static translog cost function to estimate substitution between white-collar workers, blue-collar workers and capital. According to their results, capital-skill complementarity cannot be rejected. Heterogeneous labour demand models based on educational qualifications, overviewed by Hamermesh (1993), prove that the own-wage elasticity in absolute terms decreases with the skill level. More recently, Mellander (1999) disaggregated employment in four educational qualification groups, using Swedish manufacturing data covering 20 industries. He found that the own-wage elasticity decreases with the skill level and that unskilled labour is more substitutable to capital than high-skilled labour. The cross-price elasticity between materials and unskilled labour is found to be zero. Riley and Young (1999) consider five educational qualification groups and found, however, mixed results for the ranking of own-wage elasticities by skills using cross-section time series data for the period from 1975 to 1996.

For Germany several studies employ a system of heterogeneous labour demands. The main difference to our own previous work (Falk and Koebel 1997, 1999) is that we focus on the dynamic structure of the factor demand model. In particular, the static quadratic factor demand system is reformulated as a general error correction model. As it is well known, estimates based on static factor demands are hampered by serially correlated residuals suggesting that the underlying static models are dynamically misspecified. Fitzenberger (1999) distinguished between three variable labour inputs and two quasi-fixed factors (equipment and structures) and estimated factor share equations as a multivariate partial adjustment model for the period from 1975 to 1990. He found that the demand for unskilled workers is more elastic with respect to wage changes than the demand for workers with a vocational certificate. Fitzenberger also found that unskilled labour is more substitutable to materials than medium-skilled labour. Kugler *et al.* (1989) retained a multivariate partial adjustment model using German manufacturing data from 1960 to 1986 and distinguishing between two types of capital and two types of labour. Their results suggest that substitutability between equipment and blue-collar workers is greater than between equipment and white-collar workers.[2]

II. A DYNAMIC MODEL OF LABOUR DEMAND

The most commonly used method for estimating multifactor demands is to fit *static* factor demand equations derived from the microeconomic theory of cost minimization. We assume that this relationship holds in the long-run, and may be described by a normalized quadratic cost function (see Diewert and Wales, 1987):[3]

$$c(p_{nt}, z_{nt}; \alpha_n) = p'_{nt}A_{pn} + \tfrac{1}{2}\left(\theta'_n p_{nt}\right)^{-1} p'_{nt}A_{pp}p_{nt} + p'_{nt}A_{pz}z_{nt} + \tfrac{1}{2}\left(\theta'_n p_{nt}\right) z'_{nt}A_{zz}z_{nt} \tag{1}$$

where the subscripts t and n denote time and industry, respectively, and c the total variable costs (total wage bill plus materials expenditures). Given the data available, we define the vector of variable inputs as $x_{nt} = (h_{nt}, m_{nt}, s_{nt}, u_{nt})'$ and the prices as $p_{nt} = (p_{hnt}, p_{mnt}, p_{snt}, p_{unt})'$, where h_{nt} denotes high-skilled labour, s_{nt} denotes medium-skilled labour, u_{nt} low-skilled or unskilled workers and m_{nt} total materials. Other explanatory variables entering the cost function are y_{nt}, the level of production, and k_{nt}, the net capital stock at constant prices and a time trend t denoting the impact of technological change. These variables are regrouped in a vector $z_{nt} = (k_{nt}, y_{nt}, t)'$. The matrices of parameters to be estimated, $A_{pn} = [\alpha_{pn}]$, $A_{pp} = A'_{pp} = [\alpha_{pp}]$, $A_{pz} = [\alpha_{pz}]$ and $A_{zz} = A'_{zz} = [\alpha_{zz}]$, are of size 4×1, 4×4, 4×3 and 3×3, respectively. The term $\theta'_n p_{nt}$ appearing in Equation 1 is introduced to guarantee that the cost function is linearly homogeneous in prices. The vector θ_n, of size of 4×1, is chosen to be equal to x_{n1}/c_{n1} so that $\theta'_n p_{nt}$ corresponds to a Laspeyres price index for total costs, normalized to '1' in the basis period for which $t = 1$. As underlined by Diewert and Wales (1987), this arbitrary choice of θ_n does not affect the flexibility properties of the cost function. In addition to linear price homogeneity, the price symmetry property is directly imposed on the long-run relationship Equation 1. The system of optimal input demands x^* is obtained by the application of Shepard's lemma:

$$x^*(p_{nt}, z_{nt}; \alpha_n) = A_{pn} + \left(\theta'_n p_{nt}\right)^{-1} A_{pp}p_{nt} - \tfrac{1}{2}\left(\theta'_n p_{nt}\right)^{-2}\theta_n p'_{nt}A_{pp}p_{nt} + A_{pz}z_{nt} + \tfrac{1}{2}\theta_n\left(z'_{nt}A_{zz}z_{nt}\right) \tag{2}$$

[2] Here only studies estimating a complete system of input equations are considered. In the case of Germany there are a number of studies estimating relative factor demand equations for two types of labour in the single-equation context (see Fitzroy and Funke (1995, 1998) as well as Steiner and Mohr (1998)).

[3] Recent applications of the normalized quadratic cost function can be found in Koebel (1998) or Tombazos (1999).

Furthermore, for identification purposes, the following four additional equality constraints on the matrix A_{pp} are directly imposed:

$$\iota' A_{pp} = 0 \tag{3}$$

where $\iota = (1, \dots, 1)'$. Diewert and Wales (1987) show that the price concavity property of the cost function is equivalent to the negative semidefiniteness of A_{pp}. One advantage of retaining a quadratic cost function is that, despite these restrictions, the form of Equation 1 remains flexible, which means it can still provide a local approximation for an arbitrary cost function as well as for its first and second order derivatives. Following Diewert and Wales, this system of four input demands divided by the output level x^*_{nt}/y_{nt} is considered for the estimation.

There are several approaches to incorporate dynamics in factor demand models. One approach is based on microeconomic theory, in which dynamics are introduced via time to build or via adjustment costs for some inputs. Dynamic factor demands or first order optimality conditions are then used for parameter determination. This approach requires reliable data on the user costs of capital, which is difficult to obtain for the German post-reunification period. Indeed, there is no information available about the important governmental investment support during that time.[4] To overcome these problems we treat capital as a quasi-fixed factor and use the general dynamic approach suggested by Anderson and Blundell (1982). In this case, no theoretical model is required to allow short-run input demands to differ from the optimal ones given in Equation 2. The GECM can be written as:

$$\begin{aligned} x_{nt}/y_{nt} - x_{n,t-1}/y_{n,t-1} = {} & B_1\left(x^*_{nt}/y_{nt} - x^*_{n,t-1}/y_{n,t-1}\right) \\ & + B_2(x^*_{n,t-1}/y_{n,t-1} \\ & - x_{n,t-1}/y_{n,t-1}) + \varepsilon_{nt} \end{aligned} \tag{4}$$

where both matrices $B_1(4 \times 4)$ and $B_2(4 \times 4)$ entail the unknown parameters β reflecting departure from the long-run model. The vector ε_{nt} is assumed to have zero conditional mean and a constant conditional variance. The complete model consists of 56 free parameters plus 4×26 industry dummies which have to be estimated on the basis of 26×20 observations.

There are two important issues about the estimation of the GECM. First, it is well-known that in models which are linear in parameters, the fixed effects estimator with lagged dependent variables generates biased estimates. As proved by Nickell, the bias increases in the magnitude of the adjustment coefficients and decreases with the time dimension of each cross-section. This criticism also applies to the present nonlinear GECM context where $x_{n,t-1}/y_{n,t-1}$ and ε_{nt} may be correlated. For models which are linear in parameters, Kiviet (1995) and Judson and Owen (1999) confirm in Monte Carlo studies that the bias on estimated parameters may be important, even for large T. However, Judson and Owen (1999) also found that the bias mainly concerns the coefficients of the lagged endogenous variables. Since this study focuses on price elasticities mainly depending on α_n but not on β, this issue is neglected here.

A second problem is the potential non-stationarity of the data. With 20 years for each cross-section, the time series dimension is quite large. Panel unit root tests are not applied, for two reasons. First, the time series dimension may still be too small to apply panel unit root tests. Second, given the fact that most of the variables are input-output ratios as well as relative prices, stationarity of the series is a plausible assumption. In this case, the error-correction model can still be used to distinguish between long-run and short-run effects.

Several less general dynamic models are nested within the GECM. When the matrix B_1 is diagonal, the GECM reduces to the partial ECM, and to the simple ECM when both B_1 and B_2 are diagonal. Furthermore, the GECM reduces to the static model with an autoregressive error term when B_1 is the identity matrix I_4 and $B_2 = I_4 - R$:

$$\begin{aligned} x_{nt}/y_{nt} - x_{n,t-1}/y_{n,t-1} = {} & x^*_{nt}/y_{nt} - x_{n,t-1}/y_{n,t-1} \\ & - R\left(x^*_{n,t-1}/y_{n,t-1} - x_{n,t-1}/y_{n,t-1}\right) \\ & + \varepsilon_{nt} \end{aligned}$$

For $B_2 = B_1$, the partial error-correction model reduces to the partial adjustment model considered by Nadiri and Rosen (1969):

$$x_{nt}/y_{nt} - x_{n,t-1}/y_{n,t-1} = B_1\left(x^*_{nt}/y_{nt} - x_{n,t-1}/y_{n,t-1}\right) + \varepsilon_{nt}$$

The model written in first differences is obtained when $B_1 = I_4$ and $B_2 = 0$:

$$x_{nt}/y_{nt} - x_{n,t-1}/y_{n,t-1} = x^*_{nt}/y_{nt} - x^*_{n,t-1}/y_{n,t-1} + \varepsilon_{nt}$$

Finally, the short and the long-run model coincide when $B_1 = B_2 = I_4$:

$$x_{nt}/y_{nt} = x^*_{nt}/y_{nt} + \varepsilon_{nt}$$

In the empirical part of the paper, own-price and cross-price elasticities are computed. For a given level of the capital stock, the long-run elasticities are conventionally defined on the basis of the optimal input demands x^* and therefore only depend on the parameters α_n, but not on β. The long-run price elasticities are given by:

$$\epsilon_{ip_j} = \frac{\partial i^*}{\partial p_j}\frac{p_j}{i^*} \qquad i, j = m, h, s, u$$

[4] After the German political reunification, governmental support in the form of investment bonuses, grants, extra depreciation allowances and subsidized loans has been accorded to firms investing in the eastern part of Germany.

The main hypothesis is that own-wage elasticities in absolute terms decrease with the skill level ($|\epsilon_{up_u}| > |\epsilon_{sp_s}| > |\epsilon_{hp_h}|$). Two inputs are substitutes (complements) when the cross price elasticity is significantly positive (negative). Another interesting hypothesis is that unskilled workers can be more easily substituted for materials than both medium-skilled and high-skilled workers.

The impact of capital on the variable inputs is given by:

$$\epsilon_{ik} = \frac{\partial i^*}{\partial k}\frac{k}{i^*} \qquad i = m, h, s, u$$

The sign of the partial derivative of the different labour inputs with respect to the net capital stock indicates whether a certain skill class is complementary ($\epsilon_{ik} > 0$) or substitutable ($\epsilon_{ik} < 0$) to physical capital. Capital-skill complementarity is found if the partial derivative of unskilled labour with respect to capital is higher than it is for both medium-skilled and high-skilled labour ($\epsilon_{hk} > \epsilon_{sk} > \epsilon_{uk} > 0$). Similarly, short-run elasticities can be computed from the short-run relationship given by Equation 4.

III. THE DATA

The econometric analysis is carried out for 26 manufacturing sectors for the period 1976–1995 (for details see Appendix A). The data are drawn from different sources. The nominal value and the value at constant prices of gross production, materials and the net capital stock are obtained from national accounts.[5] Employment data are provided by the German Federal Employment Office. They contain information on the number of workers by different educational qualifications and by industry for all employees paying social security contributions as of 30 June. In the original data base, nine educational qualifications are available. Labour is regrouped in three categories: Skill group 1 (also called high-skilled) is made up of workers with a university or polytechnical degree. The second skill category (medium-skilled) is assigned according to the outcome of the German vocational training system. Workers with a certificate from the dual vocational training system who have attained either an university level entrance degree ('Abitur') or a secondary school degree are categorized as medium skilled or skilled. The remaining group 3 (unskilled) consists of individuals without formal qualifications, from which we exclude apprentices. Labour is transformed into full-time equivalent workers. Further details concerning the construction of the labour inputs can be found in Appendix A.

Data on gross earnings per full-time unskilled and medium-skilled workers is obtained from a 1% random sample from the German Social Security accounts for the period from 1975 to 1995.[6] Because of the censoring problem of the wage data in the micro data, earnings of the highest skill group are taken from the German Salary Statistics. Gross wages per full-time worker are transformed into labour costs by adding the employers' contribution to social security. The sum of the three different types of labour costs is checked against total labour costs obtained from the national accounts. The exclusion of apprentices leads to labour costs at the industry level that are on average slightly below the labour costs reported in the national accounts (for details see Appendix A).

The relative decline of the number of unskilled workers in West German manufacturing before the reunification is well documented in the literature (see Fitzenberger 1999, Steiner and Mohr 1998). Few studies, however, cover the period from 1990 onwards, when the situation for unskilled labour became more severe. During the period from 1976 to 1995, the number of unskilled workers in manufacturing dropped by an average annual rate of 3.3% per year, from 3.0 to 1.6 million (see Table 1 and Fig. A1 in Appendix A).[7] For the period 1991–1995, we observe an accelerating deterioration in unskilled employment with a decline of 7% per year. In contrast, the number of full-time workers with a university degree jumped by an average annual growth rate of 3.6% over the period from 1976 to 1995. The number of university graduates, however, slightly decreased from 1993 onwards, following the severe recession in manufacturing. Medium-skilled labour grew at an annual rate of approximately one half per cent. Capital accumulation was quite moderate, with an increase of 0.8%. Therefore, it seems not likely that capital accumulation explains the shift towards skilled labour. The decreasing

Table 1. *Annual percentage changes in inputs, output, wages and prices, 1976–95*[a]

Quantities	H	S	U	K	M	Y
	3.6	0.4	−3.3	0.8	2.2	1.7
Prices	p_H	p_S	p_U	p_K	p_M	p_Y
	4.8	4.6	4.6	n.a.	1.8	2.2

Note: [a]Aggregate average growth rate over the period of 1976–1995. H, S, U, K, M denote the aggregate input quantities (aggregated into total manufacturing) in constant prices for high-, medium-, unskilled workers, capital and material inputs respectively. Y denotes the gross value of output in constant prices.
Source: Federal Labour Office, Federal Statistical Office, IAB_S, own calculations.

[5] Price indices for materials and gross output for all two digit industries for the period from 1970 to 1997 are provided by the German Statistical Office. Values in constant prices are obtained by dividing the nominal values by the corresponding price index.
[6] Average gross earnings include all amounts regularly paid to the employee (fixed or freely arranged wages, additional regular and nonregular allowances and bonuses for efficiency, social welfare, etc.).
[7] Measured as full-time equivalent workers. Apprentices are excluded.

demand for less qualified labour is matched by relatively stable wages across different types of labour (see also Fitzenberger, 1999). Since relative prices between different types of labour and materials are rather similar, the substitution patterns should explain only a small part of the changes in the labour composition. Finally, intermediate inputs (at constant prices) grew at a faster rate than gross output in constant prices. This might reflect the increasing role of services and imported materials in manufacturing.

IV. EMPIRICAL RESULTS

We start by estimating the GECM and then test the alternative less dynamic specifications. Table 2 presents the results of the log-likelihood ratio tests. It turns out that less general models such as the simple error correction, the autoregressive and the partial adjustment model are rejected by the data.

Since less general dynamic models are unable to provide a reasonable explanation of the data, the interpretation of the results focuses on the price elasticities obtained from the GECM (see Table B1 in Appendix B for the estimated parameters). To test for first order autocorrelation in the GECM, we rely on the Gauss–Newton regression described by Davidson and MacKinnon (1993, Chapter 10.8); we consider the regression

$$\widehat{\varepsilon}_{nt} = \left.\frac{\partial f}{\partial \gamma'}\right|_{\gamma=\widehat{\gamma}} C + \widehat{\varepsilon}'_{n,t-1} D + \zeta_{nt}$$

with $\gamma \equiv (\alpha', \beta')'$ and f denotes the expression on the right hand side of Equation 4. The matrix C and the diagonal matrix D are to be estimated. The residual term ζ_{nt} is assumed to have zero mean and constant variance conditionally on the regressors. Since several terms in the expression $\partial f / \partial \gamma'$ are linearly dependant, some parameters of C will not be identified and could be skipped from the regression. Estimated t-values for

$$\operatorname{diag} \hat{D} = \begin{pmatrix} \hat{d}_m \\ \hat{d}_h \\ \hat{d}_s \\ \hat{d}_u \end{pmatrix} = \begin{pmatrix} -0.142 \\ 0.081 \\ 0.010 \\ -0.044 \end{pmatrix}$$

are respectively -2.68, 1.60, 0.22 and -1.01. As first order serial correlation cannot be rejected for material inputs, the specification of the dynamic adjustment of Equation 4 may still be somewhat restrictive. Any extension in this respect entails a loss of observations, so that Equation 4 is the model we rely on.

Table 3 and Table 4 present both own-price and cross-price elasticities as well as the corresponding t-statistics. For comparison, we also present price elasticities based on the static factor demand model (see Table B2 in Appendix B). Elasticities are computed for each industry based on 1995 data. This gives us 16 price elasticities for each of the 26 industries. The range of the industry-specific price elasticities seems to be reasonable, although two outlier (shipbuilding as well as musical instruments) can be detected. To save space, we only report the median of the distribution of price elasticities among industries.

Considering own-price elasticities first, several general comments can be made. The own-price elasticities are all negative, except in the case of the short run own-price elasticity of materials as well as high-skilled labour. Labour demand for different skills is, however, quite inelastic, with long run elasticities between -0.10 to -0.21.[9] For medium-skilled labour this means that a five percent decrease in the wage rate of this group decreases the employment of medium skilled workers by only 23,000 in the long run, given a level of 4.6 million full-time equivalent workers in 1995. The short run wage elasticities range between zero for high-skilled labour and -0.09 percent for unskilled labour. This finding suggests that own wage demand elasticities decrease with the skill level; a fact that is also found by most previous studies (see Hamermesh 1993). In the long-run, however, we do not find that wage elasticities in absolute terms increase with the skill level. The median of the own-wage elasticity of

Table 2. *Test of GECM against GECM against nested specifications*

LR-Test of the GECM against	Tested hypothesis	d.o.f.	Critical value	Test stat.
Partial ECM.	B_1 diagonal	12	21.0	117.3
Simple ECM.	B_1 and B_2 diagonal	24	36.4	220.4
AR(1) model	$B_1 = I_4$ and $B_2 = I_4 - R$	16	26.3	234.1
Partial adjustment model	$B_2 = B_1$	16	26.3	914.5
First difference model	$B_1 = I_4$ and $B_2 = 0$	32	46.2	656.0
Long-run static model	$B_1 = B_2 = I_4$	32	46.2	3517.0

[9] The inelastic labour demand in German manufacturing is consistent with Flaig and Steiner (1989) who found an own-wage elasticity for aggregate labour of about -0.13.

Table 3. *Own price elasticities* (*median, 1995*)

	long-run		short-run	
	Estimate	t-value	Estimate	t-value
ε_{mp_m}	−0.103	−4.64	0.010	0.80
ε_{hp_m}	−0.206	−2.25	0.014	0.31
ε_{sp_s}	−0.101	−2.75	−0.045	−1.87
ε_{up_u}	−0.212	−1.54	−0.091	−2.03

unskilled labour with a value of −0.21 is no longer significant at the 5 percent level.[10] However, a detailed investigation of all 26 own wage elasticities reveals that there are some industries with significant own wage elasticities of unskilled labour. Thus, we conclude that in the long-run unskilled labour is also more responsive to wage-rate changes than the demand for medium-skilled labour. Using a panel of manufacturing industries over the period from 1975 to 1990, Fitzenberger (1999) also found that the negative effects of wage increases would be sharper for unskilled than for medium-skilled labour.

Table 4 presents cross-price elasticities, which also vary little in magnitude (from −0.41 for ϵ_{hp_u} to 0.48 for ϵ_{hp_m}). With the exception of ϵ_{sph1} short-run elasticities are smaller in absolute values than the corresponding long-run elasticities. Cross-wage effects between different types of labour are in general quite small. In contrast, elasticities between materials and different types of labour suggest significantly greater substitutability. The finding of complementarity between skilled and unskilled workers is surprising in the light of the empirical studies surveyed by Hamermesh (1993). However, the cross-price elasticity between skilled and unskilled labour is not robust with respect to the estimation method employed. Based on the static model, unskilled and medium-skilled labour are small but significant substitutes (see Table B2 in Appendix B). Since relative wages of various types of labour do not vary to a great extent over time, labour–labour substitution effects cannot explain the relative decline of unskilled workers.

Table 4. *Cross price elasticities* (*median, 1995*)

	long-run		short-run	
	Estimate	t-value	Estimate	t-value
ε_{mp_h}	0.011	4.05	−0.010	−1.63
ε_{mp_s}	0.047	3.89	0.014	1.93
ε_{mp_u}	0.042	4.33	−0.015	−2.01
ε_{hp_m}	0.475	2.99	−0.025	−0.81
ε_{hp_s}	−0.105	−1.00	0.064	1.83
ε_{hp_u}	−0.406	−4.23	−0.037	−1.34
ε_{sp_h}	−0.005	−1.14	0.020	2.36
ε_{sp_m}	0.146	2.93	0.001	0.09
ε_{sp_u}	−0.063	−2.72	0.007	0.85
ε_{up_h}	−0.072	−1.47	−0.084	−1.83
ε_{up_m}	0.400	1.20	0.270	4.87
ε_{up_s}	−0.223	−1.55	−0.128	−2.48

Materials can be substituted for unskilled labour, a fact which indirectly reflects the impact of foreign competition or outsourcing on the skill structure of the labour force.[11] The long run elasticities ε_{mpu} as well as ε_{upm} are positive and ε_{mpu} is strongly significant. Furthermore, in the short run the substitutability between materials and unskilled labour is stronger than any other pair of the inputs. Indeed, if firms respond to increasing import competition by moving low-skill and labour-intensive activities abroad, it is likely that material and unskilled labour become substitutes. In other words, semifinished goods (produced by foreign labour) are substituted for domestic, unskilled labour. Of course such a statement is speculative since the aggregation level of inputs does not allow us to distinguish imported materials from the remaining material. Given the size of the elasticities, one can explain the part of the shift away from unskilled labour which can be attributed to an increasing use of cheaper materials. Note that the strongest decline of the price of material is observed for the period between 1985 and 1988 with a decrease in the material deflator of about 2.2% per year. Given the short run unskilled-materials cross price elasticity of about 0.27, one third of the decrease of unskilled labour can be attributed to decreasing material prices during this period ($\epsilon_{up_m}\Delta p_{mt}/p_{mt} = 0.27 \times (-0.022) \simeq -0.006$; $\Delta u_t/u_t = -0.019$).

We find clear evidence for the hypothesis of capital–skill complementarity, which states that unskilled workers are more substitutable for capital than skilled labour (see Table 5). The derivative of high-skilled workers with respect to capital is 0.26 compared to zero for both unskilled and medium-skilled workers. For medium-skilled labour, ϵ_{sk} is small and not significant. In the short run we

Table 5. *Impact of capital on labour* (*median elasticities for 1995*)

	long-run		short-run	
	Estimate	t-value	Estimate	t-value
ε_{mr}	0.316	4.57	0.025	1.20
ε_{hk}	0.261	3.97	0.574	4.37
ε_{sk}	−0.015	−0.10	0.373	5.09
ε_{uk}	0.080	0.09	0.359	3.90

[10] Note that the own-price elasticity of unskilled workers based on the static model is clearly higher with a value of −0.38 and significant at the 5% level (see Table B2 in Appendix B). In contrast, the first difference model clearly underestimates the own-price elasticity of all three types of labour; the values are $\epsilon_{upu} = -0.11$, $\epsilon_{sps} = -0.02$ and $\epsilon_{hph} = 0.06$ with t-values of −2.8, −1.2 and 1.1, respectively.

[11] A detailed disaggregation of materials based on the German cost structure statistics indicates that intermediate services and intermediate imports are gaining more importance compared to energy and intermediate domestic materials.

also observe that the effect of capital accumalation on labour demands depends on the skill level. Given the impact of capital on high-skilled labour, one can compute to what extent the demand for high-skilled labour can be explained by capital accumulation. The calculation suggests that over the period from 1976 to 1995, capital accumulation can explain between 6 and 13% of the increase in high-skilled labour ($0.57 \times 0.008 \simeq 0.0046; 0.26 \times 0.008 \simeq 0.0021$; $\Delta H_t / H_t = 0.036$).

V. CONCLUSION

A multivariate ECM was estimated for heterogeneous labour demands, allowing for a dynamic adjustment process for each variable factor. The econometric study focuses on the determinants of heterogeneous labour demands: own-wage elasticity, substitution possibilities, impact of capital and materials. Based on West German industry data over the period 1976 to 1995, it was found that the GECM performs well on statistical grounds. First, labour demands for different skill classes are inelastic, both in the short and long run. However, the demand for unskilled labour is more price elastic than the demand for both medium-skilled and high-skilled labour at least in the short run. This explains a part of the demand shifts away from unskilled labour. Second, we find that materials are a substitute for unskilled labour, with a short run and long run cross price elasticity of 0.27 and 0.40, respectively. Despite some temporary falls in the input prices of materials, unskilled labour-material substitutability only explains a small part of the shift in demand away from low-skilled employment. Third, capital accumulation alone can only account for less than 13% of the shift in demand towards high-skilled labour. Briefly, no impact clearly dominates, it is rather the conjunction of these three impacts that is responsible for the observed fall in the demand for unskilled labour.

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APPENDIX A: DATA DESCRIPTION AND DESCRIPTIVE STATISTICS

Materials, output, price deflators and net capital stock

National account data provide gross output, total material at nominal prices as well as the net stock of capital at constant prices for all two digit West German manufacturing industries. Disaggregated material prices as well as gross output price indices are available for the commodity classification given in the input-output tables.

Wages and employment for different skill groups

The main data source for the labour inputs is the German Social Security accounts provided by the German Labour Office. The data for the wages are mainly drawn from the I_ABS which has been made available by the research institute of the Federal Labour Office in October of 1999. Employment data are available for the period from 1976 to 1998, but since the net capital stock as well as earnings are only available until 1995, our sample spans from 1976 to 1995. Note that the industry classification differs slightly from the national accounts. In some industries, only aggregate information covering two industries is available (Paper (37/38); Rubber (17) and Petroleum refining (15) are added to the chemical industry (14)). This leaves us with 29 manufacturing industries. We further decided to exclude aircraft (30), tobacco (45) and office machinery (27). The latter is excluded because of the structural break in the employment data (40% decrease in 1993). Aircraft (30) as well as tobacco (45) are excluded because of the small cell size in the I_ABS.

Labour input by education is constructed in multiple steps. Since the industry classification based on the Employment Statistics covers 159 industries and therefore is more detailed than national accounts data, we aggregate employment of different types of skills into 32 industries. For approximately 5% of the workers there is no information about their educational qualifications. This percentage depends on the industry and ranges between 0% in aircraft and 8% in minerals. We assume that most of these workers did not complete university or vocational college education and add 2/3 of these workers to the unskilled group and 1/3 to the medium-skilled group.[12] The next step is to exclude apprentices from the unskilled group.[13] From the I_ABS data we calculate the share of apprentices as a percentage of all workers for each sector and then subtract the corresponding number of apprentices from unskilled labour. Apprentices represent about 4% of total labour in 1995, or about 14% of unskilled labour. Finally, the number of workers is transformed into the number of full-time equivalent workers. This is done by weighting part-time workers with one half. For each skill group the part-time workers' share is calculated from the I_ABS data (Employment Statistics of the Institute for Employment Research). Note that the share of part-time workers in total workers is higher for unskilled workers than for both medium- and high-skilled labour: It ranges between 17% in wearing apparel and 0.3% in iron and steel. For medium-skilled workers the part-time ratio ranges between 12% in wearing apparel and 0.2% in iron and steel.

Earnings are drawn from the 1% random sample from the Social Security accounts. Median monthly wages are extracted for workers with a vocational degree and workers without any degree as of 30 June. Apprentices are excluded from the unskilled group. For manufacturing the number of cases is 14 164 for unskilled workers and 32 808 for medium-skilled workers (data for 1995). Gross wages for high-skilled workers are drawn from the Wage and Salary Statistics and are only available for full-time female and male workers separately. The highest skill group refers to 'professional and managerial workers' (category II white-collar). An average wage of high-skilled workers is calculated as a weighted mean of the average wage of females and males (using the shares of females and males as weights). Earnings for all skill classes are converted into labour costs by adding the employers' part of social security contribution.

There are two important issues concerning the labour input. The main reason for not considering more disaggregated types of workers (by gender or experience for instance) is that in some industries the cell size would then become too small. For example, in shipbuilding, the number of women with a vocational certificate is less than 10. Another problem of the I_ABS is a structural break in the data (see Steiner and Wagner, 1998). From 1984 onwards, more and more one-time income components (such as bonuses) are added to labour earnings. As noted by Steiner and Wagner (1998), this results in a considerable increase in the wage data starting from 1984 (see also Fitzenberger, 1999). To check the reliability of the wage data we also extracted wage data based on the German Wage and Salary Statistics. Here the term 'Unskilled labour wages' refers to category III for the blue-collar group and the category V for the white-collar group. Wage data in both categories contain employees without any formal degree. 'Medium-skilled labour wages' refers to category I (vocational training and foreman) for the blue-collar group and to categories III and IV for the white-collar group. We experimented with both data sources (I_ABS and the wage and salary statistics). However, comparing wages drawn from the wage and salary statistics with I_ABS data, we find little differences between these two data sources. Furthermore, the econometric results

[12] A conversation with the Federal Labour Office supports this conjecture.
[13] For apprentices it does not seem reasonable to assume Shephard's lemma to hold.

are robust with respect to the data sources (see also Falk and Koebel, 1998, for the period from 1978 to 1990).

Table A1 gives an overview of the relevant variables used to construct the labour inputs as well as the employment shares. Table A2 gives an overview of the input quantities and Table A3 of the corresponding inputs prices at the sectoral level.

Table A1. *Employment shares, apprentices and part-time ratio* (*1995*)

		part-time ratio		apprentices	employment shares[a]		
Code	Industry	S	U	in % of U	H	M	U
14/15/17	Chemicals, Petrol, Rubber	2.2	4.4	11.5	11.3	67.9	20.8
16	Synthetic material	2.5	6.2	4.2	3.5	58.7	37.8
18	Stone & earth products	0.9	1.4	5.3	3.5	66.3	30.2
19	Fine ceramics	2.4	9.2	4.3	3.8	50.3	45.9
20	Glass	1.3	3.5	7.1	4.8	61.3	33.9
21	Iron & steel	0.2	0.3	10.6	5.1	66.3	28.6
22	Non-ferrous metal	1.4	3.6	7.2	5.3	62.6	32.1
23	Foundry	0.3	1.4	7.3	2.9	58.4	38.8
24	Fabricated Metals	1.3	3.0	9.5	2.3	66.8	30.9
25	Steel, light metal	0.4	1.8	23.6	5.8	80.7	13.5
26	Machinery	0.7	3.5	23.1	8.4	79.9	11.8
28	Vehicles & repairs	1.5	1.8	18.2	5.3	75.2	19.5
29	Shipbuilding	0.9	2.5	37.5	8.0	84.1	8.0
31	Electrical machinery	2.0	8.2	14.6	13.8	64.1	22.1
32	Precision & optical instru.	3.6	8.3	28.9	6.1	78.2	15.6
33	Metal products	1.6	4.2	6.9	3.4	62.9	33.6
34	Musical instruments	7.1	11.4	8.9	1.6	65.9	32.5
35	Wood	2.0	2.5	6.0	1.7	53.5	44.9
36	Wood processing	1.4	4.3	26.4	1.6	76.8	21.6
37/38	Paper	0.6	3.3	7.5	3.5	60.8	35.7
39	Printing & duplicating	2.2	6.6	18.5	2.6	78.4	19.1
40	Leather	6.7	8.0	4.4	2.1	56.0	41.9
41	Textile	11.6	11.6	5.1	3.0	54.1	43.0
42	Clothing	11.8	17.1	8.6	1.6	66.8	31.6
43	Food	6.0	7.8	16.3	1.8	72.5	25.8
44	Beverages	1.7	4.2	9.0	3.6	73.8	22.7

Note: [a] Employment shares are based on full-time equivalent workers.
Source: Federal Labour Statistics, I_ABS, own calculations.

Table A2. *Evolution of quantities by industries, 1976–1995*[a]

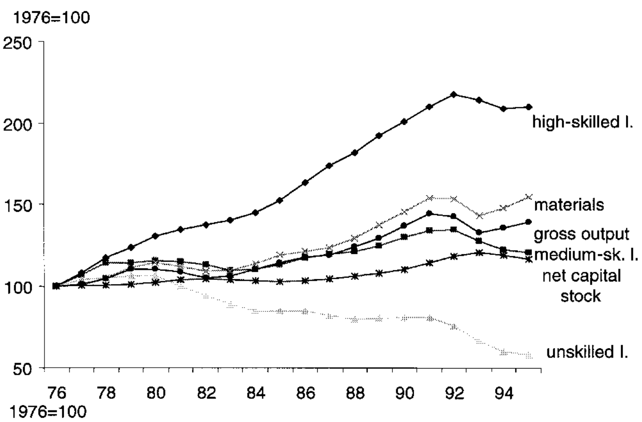
	Industry	*h*	*s*	*u*	*m*	*k*	*y*
14/15/17	Chemicals, Petrol, Rubber	2.9	0.4	−4.3	2.7	−0.1	2.2
16	Synthetic material	6.9	3.3	−0.1	5.4	4.4	4.9
18	Stone & earth products	2.2	0.1	−2.9	0.3	−0.2	0.3
19	Fine ceramics	3.3	−0.3	−3.2	2.3	−0.8	−0.3
20	Glass	3.7	0.6	−3.5	3.2	1.2	2.5
21	Iron & steel	−1.5	−4.0	−7.1	−0.1	−3.4	−0.3
22	Non-ferrous metals	2.3	0.2	−3.7	2.6	0.1	2.4
23	Foundry	1.9	−1.0	−3.2	0.4	−0.7	−0.2
24	Fabricated Metals	4.3	1.6	−1.6	1.9	0.3	1.8
25	Steel, light metal	4.3	0.6	−3.0	1.1	0.8	1.1
26	Machinery	3.1	0.0	−4.2	0.7	1.0	0.3
28	Vehicles & repairs	5.9	1.5	−2.4	3.8	3.1	3.1
29	Shipbuilding	0.1	−4.3	−10.0	−1.6	−1.4	−2.3
31	Electrical machinery	3.7	0.6	−3.9	4.0	3.0	3.2
32	Precision & optical instrum.	4.9	1.5	−4.4	2.0	2.4	0.9
33	Metal products	5.7	1.2	−2.1	3.0	1.4	2.3
34	Musical instruments	2.0	−0.7	−3.8	2.8	1.5	1.6
35	Wood	3.6	0.6	−2.6	1.9	−0.8	1.7
36	Wood processing	4.8	0.8	−3.0	1.6	−0.2	0.6
37/38	Paper	4.4	1.3	−2.8	3.2	2.3	2.5
39	Printing & duplicating	4.4	0.6	−1.8	2.7	2.2	1.9
40	Leather	5.5	−1.8	−6.2	−1.8	−3.0	−2.8
41	Textile	0.9	−2.5	−6.1	−1.1	−2.0	−1.9
42	Clothing	1.8	−3.6	−6.9	−0.1	−2.3	−1.2
43	Food	4.2	0.9	−1.2	1.8	0.2	1.6
44	Beverages	1.9	−1.4	−4.2	1.5	0.0	0.5

Note: [a] Average annual growth rate over the period 1976–1995.

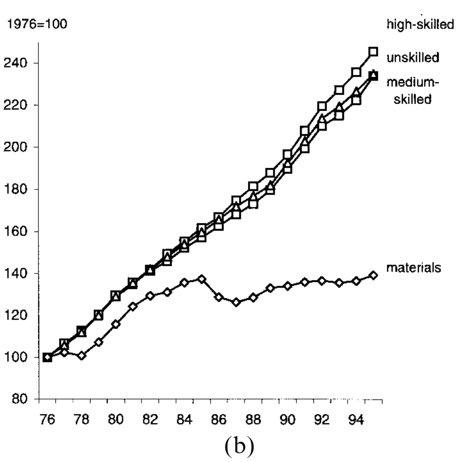
Table A3. *Evolution of input prices by industries, 1976–1995*[a]

	Industry	p_h	p_s	p_u	p_m
14/15/17	Chemicals, Petrol, Rubber	5.0	5.1	4.7	0.8
16	Synthetic material	4.5	4.3	4.8	1.7
18	Stone & earth products	4.5	4.4	4.4	3.1
19	Fine ceramics	4.3	4.6	4.0	2.0
20	Glass	4.6	4.4	4.5	1.4
21	Iron & steel	4.3	4.7	4.4	0.4
22	Non-ferrous metals	4.9	4.5	4.4	0.7
23	Foundry	4.6	4.5	4.5	2.4
24	Fabricated Metals	4.6	4.1	4.1	1.7
25	Steel, light metal	4.7	4.0	4.1	3.6
26	Machinery	4.9	4.7	4.5	3.1
28	Vehicles & repairs	4.7	4.9	4.8	3.1
29	Shipbuilding	4.9	4.6	4.7	2.8
31	Electrical machinery	5.0	4.7	5.0	1.5
32	Precision & optical instrum.	4.7	4.3	4.5	2.3
33	Metal products	4.6	4.4	4.7	2.3
34	Musical instruments	4.7	3.9	4.4	1.7
35	Wood	4.5	4.7	4.4	1.2
36	Wood processing	4.5	4.2	4.5	3.0
37/38	Paper	4.9	4.5	4.8	1.8
39	Printing & duplicating	4.7	4.9	5.1	2.5
40	Leather	4.6	3.8	5.0	2.7
41	Textile	4.6	4.2	4.4	1.1
42	Clothing	4.7	4.7	4.5	2.0
43	Food	4.8	3.9	4.5	0.3
44	Beverages	4.6	4.7	4.4	1.7

Note: [a]Annual average growth rate over the period 1976–1995.



(a)



(b)

Fig. A1. (*a*) *Quantities manufacturing 1976–95;* (*b*) *input prices manufacturing 1976–95*

APPENDIX B: FURTHER ESTIMATION RESULTS

Table B1. *Parameter estimates from the GECM*

	Estimates	t-value		Estimates	t-value
β_{1hh}	1.603	3.41	α_{hk}	0.003	0.61
β_{1hm}	0.031	1.41	α_{hs}	−0.039	−1.23
β_{1hs}	0.497	4.55	α_{ht}	0.006	4.62
β_{1hu}	−0.915	−4.31	α_{hu}	−0.127	−5.00
β_{1mh}	8.042	2.53	α_{hy}	0.006	2.26
β_{1mm}	−0.001	−0.01	α_{kk}	0.000	0.05
β_{1ms}	0.549	0.61	α_{kt}	0.009	3.95
β_{1mu}	−2.367	−1.28	α_{ky}	0.001	1.15
β_{1sh}	0.142	0.07	α_{mh}	0.228	4.42
β_{1sm}	0.283	2.33	α_{mk}	0.304	4.05
β_{1ss}	1.601	2.55	α_{ms}	1.101	4.07
β_{1su}	−1.111	−0.96	α_{mt}	−0.056	−2.56
β_{1uh}	−5.076	−2.29	α_{mu}	0.926	4.54
β_{1um}	0.125	1.33	α_{my}	0.307	4.39
β_{1us}	−1.910	−3.76	α_{sk}	−0.046	−1.05
β_{1uu}	4.426	5.14	α_{st}	−0.022	−2.06
β_{2hh}	0.119	6.76	α_{su}	−0.411	−3.78
β_{2hm}	−0.001	−1.30	α_{sy}	0.081	2.59
β_{2hs}	−0.004	−1.76	α_{tt}	−0.001	−1.84
β_{2hu}	0.005	3.29	α_{uk}	−0.017	−0.63
β_{2mh}	−0.274	−1.06	α_{ut}	−0.005	−0.73
β_{2mm}	0.105	5.49	α_{uy}	−0.007	−0.25
β_{2ms}	−0.092	−2.49	α_{yt}	0.010	5.97
β_{2mu}	−0.020	−0.60	α_{yy}	−0.001	−2.10
β_{2sh}	0.674	5.30			
β_{2sm}	−0.054	−7.39			
β_{2ss}	0.073	4.57			
β_{2su}	0.035	2.42			
β_{2uh}	−0.110	−1.12			
β_{2um}	−0.038	−6.30			
β_{2us}	0.040	3.05			
β_{2uu}	0.048	3.94			

Notes: 4×26 Industry dummies are included but not reported. β_{1ij}, and β_{2ij}, $i, j = h, m, s, u$, are elements of both the B_1 and B_2 matrix.

Table B2. *Price elasticities and impact of capital, static model* (*median elasticities for 1995*)

	Estimates	t-value
ε_{mp_m}	−0.008	−0.88
ε_{hp_h}	−0.065	−0.62
ε_{sp_s}	−0.092	−2.35
ε_{up_u}	−0.380	−2.89
ε_{mp_h}	0.003	2.68
ε_{mp_s}	−0.003	−0.44
ε_{mp_u}	0.006	0.85
ε_{mk}	−0.012	−1.06
ε_{hp_m}	0.133	2.62
ε_{hp_s}	−0.194	−2.05
ε_{hp_u}	0.113	1.04
ε_{hk}	0.370	5.40
ε_{sp_m}	−0.018	−2.05
ε_{sp_h}	−0.011	−0.45
ε_{sp_u}	0.089	3.02
ε_{sk}	0.239	4.95
ε_{up_m}	0.024	1.01
ε_{up_h}	0.065	0.90
ε_{up_s}	0.279	2.94
ε_{uk}	0.619	5.51