struc3.doc.981203

STRUCTURAL CHANGE, COMPETITION AND JOB TURNOVER IN THE SWEDISH MANUFACTURING INDUSTRY 1964-96

By

Linda Andersson[1] **Ola Gustafsson**[2] **Lars Lundberg**[3]

Abstract

The rate of inter-industry job turnover in Swedish manufacturing seems to be driven by the dispersion of profit changes among industries. Shifts in international competitiveness among industries played a central role for explaining this pattern. The rate of intra-industry job turnover among plants has been higher in industries with many small plants, low profit margins and high import penetration.

JEL: F10, J63

Keywords: comparative advantage, market power, structural change, job turnover

Not to be quoted. Comments are welcome.

[1] Umeå University
[2] Trade Union Institute for Economic Research
[3] Trade Union Institute for Economic Research and Umeå University

1 Background and scope of the paper

A sufficient degree of mobility of factors of production among firms and industries is often seen as a precondition for maintaining an efficient resource allocation in an economy facing a changing economic environment. Structural change is reflected in the labor market by reallocation of jobs among firms and industries, and possibly also by different trends in the demand for, and rewards to, groups of workers differing with respect to level and type of skill.

In a broad sense, structural change may include not only changes in the industry composition of output and employment, but also redistribution of employment and market shares among firms within the same industry, or even changes within firms, e.g concentration to fewer products or introduction of new technology and products. In this paper, we use the term structural change in the limited sense of rate of job turnover, i.e. rates of change of the distribution of employment among industries and plants.

In a closed economy – or in sectors producing non-traded goods and services – the structure of employment and output will be determined by domestic demand and supply. In general, in a growing economy one should expect increasing shares of total employment in sectors where demand is highly elastic with respect to income. A high rate of growth of productivity will work both ways. On the one hand it will decrease costs and prices and thus increase demand; on the other, given output, demand for labor will fall.

In the traded goods and services sectors, the structure of employment is determined not only by the rate of growth of demand – in this case it is world, not domestic, demand that is relevant – but also by changes in international competitiveness of domestic producers. Employment will shift towards industries with a high rate of growth of demand where domestic firms are able to increase their market shares on export markets as well as on the home market.

Moreover, jobs are reallocated among firms within the same industry, in response to firm specific shifts in demand or technology. The frequency of such demand and supply shocks, as well as the response to them, may depend on the characteristics of the market – such as the degree of competition and market power of sellers – and of the production process.

The scope of this paper is to analyze the determinants of the rate of structural change, defined as the rate of job turnover, i.e. the rate of change in the distibution of employment, among industries as well as among plants within the same industry. In particular, the paper will focus on the role of competition – both national and international - as a driving force behind structural adjustment. We begin by definining the concepts of structural change and job turnover, and present models explaining structural change and job turnover in an open economy.

Since we want to explore the role of international competition for structural change, and since most markets for services have, until recently, been virtually closed to international trade, the study is limited to employment in the manufacturing industry. For data reasons, the empirical analysis is separated into two parts. The first attempts to explain the time pattern of the rate of inter-industry job turnover in manufacturing. The second part focuses on the variation across industries with respect to the rate of intra-industry reallocation of employment among plants.

2 Job turnover and structural change

Following Davis et al. (1996) we define job creation and job destruction as changes in employment on the plant level. On the industry level, job creation in the *i*th industry is defined as the sum of employment changes in expanding plants, including entries, whereas job destruction is the sum of employment changes in contracting (including exits) plants[1]:

$$C_{it} = \sum_{j\in +} dL_{ijt} \qquad\qquad D_{it} = \sum_{j\in -} \left| dL_{ijt} \right| \tag{2.1}$$

where $\sum_{j\in +}$ denotes summing over plants in the group of expanding plants. Dividing with employment gives the rates of job creation and destruction:

$$c_{it} = \frac{C_{it}}{L_{it-1}} \qquad\qquad d_{it} = \frac{D_{it}}{L_{it-1}} \tag{2.2}$$

[1] See also Davidsson et al. (1996) and Zetterberg (1997).

The rate of intra-industry gross job reallocation among plants, also called job turnover, is the sum of the rates of job creation and destruction in the *i*th industry:

$$r_{it} = c_{it} + d_{it} = \sum_{j=1}^{n_i} \left| \frac{L_{ijt} - L_{ijt-1}}{L_{it-1}} \right| \tag{2.3}$$

The overall rate of job reallocation in the economy may be written as a weighted average of the r_{it} s:

$$r_t = L_{t-1}^{-1} \sum_{i=1}^{n} \sum_{j=1}^{n_i} \left| L_{ijt} - L_{ijt-1} \right| = \sum_{i=1}^{n} a_{it-1} r_{it} \tag{2.4}$$

where a_{it-1} is the share of total employment of the *i*th industry in period *t*-1.

The variables r_t and r_{it} will reflect the rate of growth of employment. In this paper we focus on explaining the rate of *net* job reallocation, in the sense of the rate of redistribution of a *given* total employment, among plants and industries. We use a measure based on changes of *shares* of employment of industries and plants, rather than changes in the number of jobs.

Data for employment by plant are only available for a limited period, whereas employment by industry may be obtained for a much longer period. As a consequence, the empirical analysis is divided into two parts. In the first, we calculate an indicator of the rate of structural change of employment among industries within manufacturing – the rate of net inter-industry job turnover - by summing the absolute values of the annual changes in employment shares by industry:

$$\sigma_t = \sum_{i=1}^{n} \left| a_{it} - a_{it-1} \right| \tag{2.5}$$

where $a_{it} = \frac{L_{it}}{L_t}$ is the share of the *i*th industry of total employment in manufacturing in year *t* and *n* the number of industries. This figure measures the rate of inter-industry job reallocation as a proportion of total employment. The level of σ depends on the level of aggregation: the more detailed data, the higher σ will be.

A measure of within-industry job reallocation among plants may be obtained in the same way. From one year to another, some plants will close down, while others will enter. Define the share of employment in the ith industry of the jth plant at time t as $a_{ijt} = \frac{L_{ijt}}{L_{it}}$. The rate of intra-industry job reallocation may then be obtained by summing the absolute value of changes in employment shares across all plants in the industry – expanding as well as contracting. Let a_{ijt}^{e} be the employment share of a new plant entering the industry, i.e. which exists in year t but not in t-1, a_{ijt-1}^{x} the share of a plant closed down (existing in t-1 but not in t), and $(a_{itj}^{b} - a_{ijt-1}^{b})$ the change of the employment share for a plant existing in both periods, hereafter called an existing plant. Then the rate of net intra-industry job turnover may be written

$$\mathrm{s}_{it} = \sum_{j=1}^{b_i} \left| a_{ijt}^{b} - a_{ijt-1}^{b} \right| + \sum_{j=1}^{e_i} a_{ijt}^{e} + \sum_{j=1}^{x_i} a_{ijt-1}^{x} \tag{2.6}$$

where b_i, e_i, x_i are the number of plants existing in both periods, the number of plants entering and the number of plants exiting from the ith industry. The first term shows the role of reallocation of workers among existing plants, and the second and third the contribution to intra-industry job mobility from entry and exit of plants.

Comparing the two measures of gross and net intra-industry job turnover, i.e. r_{it} and s_{it}, we note that they are identical only if L_{it} is constant. If, say, employment in all plants grew at the same rate, s_{it} would be zero but r_{it} positive. In fact, our net job reallocation measure s_{it} is obtained by eliminating the effect of the rate of net employment growth from the gross job reallocation rate in (2.3):

$$\mathrm{s}_{it} = \sum_{j}^{n_i} \left| \frac{L_{ijt}}{L_{it}} - \frac{L_{ijt-1}}{L_{it-1}} \right| = \sum_{j}^{n_i} \left| \frac{g_{it}^{-1} L_{ijt} - L_{ijt-1}}{L_{it-1}} \right| = g_{it}^{-1} r_{it} \tag{2.7}$$

where $g_{it} = L_{it} / L_{it-1}$. In this paper, we will focus on the concept of net job reallocation or net job turnover, i.e. on s. We will use the terms inter- and intra-industry job turnover (reallocation) in this sense.[2]

3 A model for explaining inter-industry structural change

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[2] This paper studies *job* turnover but not *labor* turnover, the mobility of individual workers (i.e. the gross flows on the labor market). For studies of labor mobility in Sweden – geographical and/or occupational – see e.g. Holmlund (1984) and Blomskog (1997).

The actual rate of inter-industry job turnover and structural change is a result of the interaction of adjustment pressure and adjustment resistance. The former works through changes in prices and market growth as well as changes in international competitiveness of domestic producers, giving an incentive to increase or reduce employment. The latter includes all kinds of barriers to labor mobility. Thus an increase in the actual rate of inter-industry job turnover could be caused by increased adjustment incentives or decreased resistance or both. A comprehensive analysis of the role of factors influencing adjustment resistance and barriers to labor mobility is, however, outside the scope of this paper.[3]

Focusing on the role of adjustment pressure, the rate of inter-industry structural change in a small open economy may be analyzed by means of a simple model, the so called specific factors or Ricardo-Viner model. Assume that all industries are producing a homogeneous good using two factors of production: labor *L*, which is perfectly mobile across sectors, implying equal wage rate *w* across sectors, and capital K_i, which is immobile – i.e. sector specific - in the short run. All goods are traded on the world market at given prices p_i. Perfect competition in all markets implies that labor demand in each industry is determined by the profit maximization condition

$$w = p_i t_i f_L^i(L_i, K_i) \qquad (3.1)$$

where t_i is a technology parameter and $t_i f_L^i(L_i, K_i)$ the marginal productivity of labor (suppressing the time index) . In the short run where the K_i :s are fixed, labor demand depends on product price, wage rate and technology:

$$L_i = L^i(p_i, w, t_i) \qquad (3.2)$$

From (3.1) it is clear that technological progress dt_i will have exactly the same effect on labor demand as a price increase dp_i. Thus it is sufficient to derive the effects of price changes in the Appendix.

Define the elasticity of demand for labor l_i by the expression

$$\hat{L}_i = l_i(\hat{p}_i - \hat{w}) \qquad (3.3)$$

[3] For an international comparison relating rates of job turnover to national market rigidities see Salvanes (1997).

where $\hat{L}_i, \hat{p}_i, \hat{w}$ indicate rates of change: note that λ_i is defined to be positive. For total employment constant, the change in the share of employment of the *i*th industry will be

$$da_i = a_i \hat{L}_i \tag{3.4}$$

Assume that world market prices p_i change. Then employment will increase in sectors where prices rise more than the wage rate. Neglecting differences among sectors in elasticity of labor demand (i.e. set all $\lambda_i = \lambda$), we show in the Appendix that employment shares will increase in all industries where the price increase is above average, and fall in all other sectors. The increase of the share will be larger the more the price has gone up. We have that

$$da_i = a_i \lambda (\hat{p}_i - \hat{w}) = a_i \lambda (\hat{p}_i - \sum_{i=1}^{n} a_i \hat{p}_i) \tag{3.5}$$

Inserting this into our measure of inter-industry job turnover we obtain (inserting the time index)

$$\sigma_t = \sum_{i=1}^{n} |da_{it}| = \lambda \sum_{i=1}^{n} a_{it} \left| \hat{p}_{it} - \sum_{i=1}^{n} a_{it} \hat{p}_{it} \right| \tag{3.6}$$

The more price changes *differ* among industries, the higher will be the rate of structural change and job mobility. If all prices change in the same proportion there will be no structural change. The same holds for technical change: the larger the *dispersion* among industries with respect to the rate of technical progress, the more job turnover.

In the empirical application we have no data for world prices or the technology parameters. However, there are data for gross profit margins by industry, defined as

$$\pi_i = 1 - \alpha_i \tag{3.7}$$

where α_i is wages share of value added. We therefore proceed, in the Appendix, to derive the link in our model between the unobservable price changes and technology shifts and the observable changes in gross profit margins, noting that technical progress will have the same effects as a price increase. This leads us to the following equation for the rate of inter-industry job turnover, expressed in terms of changes in gross profit margins:

$$\sigma_t = \sum_{i=1}^{n} |da_{it}| = \sum_{i=1}^{n} a_{it} \left| \frac{d\pi_{it}}{\alpha_{it}^2} - \sum_{i=1}^{n} \frac{a_{it} d\pi_{it}}{\alpha_{it}^2} \right| = \theta_t \tag{3.8}$$

The rate of reallocation of employment among industries is proportional to a weighted measure of the dispersion of changes in gross profit margins among industries. Thus, the larger the differences among industries with respect to price changes and technical progress, the more variation in changes of gross profit rates, and the more job turnover there will be.

Equations (3.6) and (3.8) show the short run effects on job turnover. However, changes in *p* and *t* will affect the return to capital in each sector. In the longer run this will lead to a reallocation of capital. In general, capital will be reallocated towards industries where rates of return have increased, that is, according to the previous analysis, towards industries with high rates of technical progress and/or rising world market prices. This will reinforce the short run effects. The time profile of the long term rate of adjustment depends, among other things, on the rate of depreciation of capital.

The role of openness for inter-industry reallocation may be demonstrated within the setting of the specific factors model. Assume now that only n_T goods are traded on the world market at given prices, while $n_S = n - n_T$ industries are sheltered from foreign competition. Assume further that the economy is exposed only to exogenous shocks in the form of changes in world prices. For simplicity, let the pattern of price changes be such that the (weighted) mean is zero, which means that the wage does not change (se Appendix). If so, there is no reason why prices and profit margins in the sheltered sector should change. From (3.8), the rate of job reallocation is

$$\sigma = \theta = \lambda \sum_{i=1}^{n} a_i \left| \frac{d\pi_i}{\alpha_i^2} \right| \qquad (3.9)$$

But since $d\pi_i = 0$ for all industries in the sheltered sector, it must hold that, given world market prices, θ will be higher if the economy becomes more open, in the sense that industries change status from the sheltered to the traded sector.

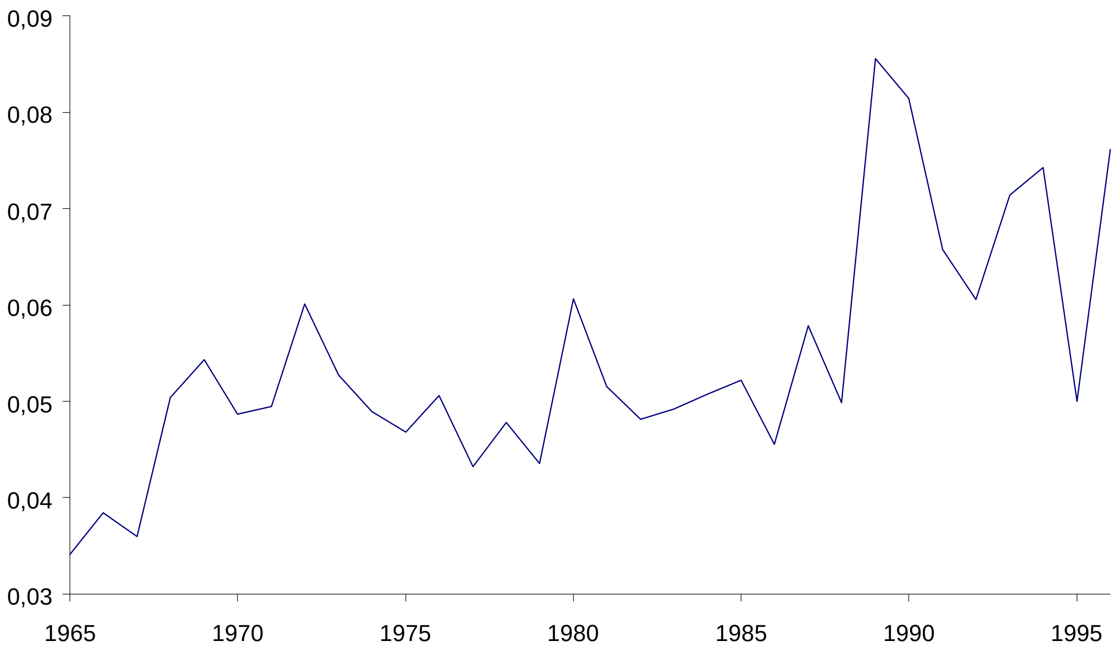
This holds also if we assume that shocks enter in the form of domestic technical progress. Other things equal, an increase in t_i has a larger effect on employment in an industry trading at given world market prices than in a sheltered industry. This is so because in the latter case the positive shift of the supply curve leads to a price fall which counteracts the initial effect on the demand for labor. Again, for a given pattern of shocks, inter-industry job turnover will increase over time with the degree of internationalization, in the sense that more goods become tradeable.

4 Inter-industry job turnover in Swedish manufacturing 1964-96

The structure of total employment in Sweden has shifted over the past decades away from industry in favor of services, in particular towards the public sector. The share of manufacturing fell from 30% in 1960-65 to 19% in 1990-95 (OECD 1997).

Within the manufacturing sector, jobs have mainly been reallocated away from traditional, natural resource based and export oriented sectors such as the paper, sawnwood and steel industries, but also from labor intensive activities such as production of wearing apparel and shoes. In certain sectors, changes have been dramatic. For shipyards, employment fell to about one third of the level before the first oil price shock. For clothing, employment gradually decreased by 80% during a 40-year period.

Figur 4.1 Inter-industry job turnover in Swedish manufacturing 1964-96 (percent)



A more comprehensive picture of the time pattern of Swedish industrial restructuring may be obtained from Figure 4.1, which shows the annual rate of structural change within Swedish manufacturing 1964-96, defined as the rate of inter-industry job turnover, s_t, calculated according to (2.5) from data on the most detailed level of the SNI, the Swedish industrial classification system. A description of data sources and methods of calculation is given in the Appendix.

The mean of the σ_t series (in %) is 5.4, which means that, on average, 2.7% of the stock of jobs in manufacturing has been reallocated among industries each year.[4] This, of course, only captures a minor part of total labor mobility, since neither intra-industry turnover of jobs among plants, nor gross flows of workers, are included.

The rate of structural adjustment defined in this way has apparently increased during the last 30 years. The trend is positive and strongly significant. However, this conclusion rests mainly on the first (1965-68) and last (1989-96) years of the period – if these are excluded the trend disappears. Moreover, the volatility of the annual rate of industrial restructuring seems to be higher towards the end of the period, making the trend less stable (see Appendix).

In the popular debate, the mid-1970s, after the first oil price shock, is usually seen as a period where the pressure for industrial restructuring was particularly intense. This impression seems to be based on the dramatic development in certain industries such as steel mills and shipyards, and was probably reinforced by the fact that the "structural crisis" involved very large plants which dominated local or even regional labor markets. However, this picture is not confirmed by Figure 4.1. In a historical perspective the mid-1970s does not seem to be a period of a particularly high rate of inter-industry job turnover.

5 Determinants of the rate of inter-industry job turnover

The conclusion from section 3, where we presented our model for explaining the rate of inter-industry structural change and job turnover, was that σ_t was determined by θ_t, a weighted measure of the dispersion of changes in profit margins among industries.[5] In addition, the time pattern of σ_t may be related to a number of macroeconomic variables reflecting the business cycle and/or excess demand and supply on the labor market.

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[4] Since, assuming total manufacturing employment constant, a worker moving from one industry to another will be counted twice.

[5] Note that the particular form in (3.19), i.e. the equality $\sigma = \theta$, is a feature of the particular model used in section 3. In the empirical application we use the more general formulation $\sigma = a + b\theta$.

Granted that our variable q actually measures incentives/pressures to structural change, the response may vary with macroeconomic conditions. Even so it is far from obvious whether the pattern is pro- or countercyclical. One may argue that the pull component of adjustment pressure – i.e. demand for additional workers from expanding sectors – may be relatively strong when there is excess demand for labor, whereas the push component – workers made redundant in contracting sectors – may dominate in recessions. According to Davis et al. (1996), job destruction in the U.S. industry tends to increase strongly in recessions, whereas job creation is more stable, thus leading to a countercyclical pattern of job reallocation.

To capture the effects of general labor market conditions we have used two alternative proxies, namely the ratio of unemployment to vacancies, *U/V* and the rate of change of industrial employment $\hat{L}$ (in the terminology of Davis et al. (1996), the rate of total net job creation). In the late 1980s the labor market was overheated, with open unemployment rates below 2% (OECD 1997). However, the economic climate changed drastically in the beginning of the 1990s, and the Swedish economy found itself in a deep recession. Overall unemployment rose to over 8%, and in a few years one out of five manufacturing jobs was lost.

Moreover, it seems likely that industrial policy has affected the rate of inter-industry job turnover. After the first oil price shock, the international recession, a steep increase in Swedish relative wage costs and pressure from new producers brought a number of large firms, in particular shipyards and steelmills, close to bankruptcy. To avoid the negative impact on local or regional labor markets, i.e. to preserve jobs in these firms, there was a strong increase in various kinds of selective subsidies (Carlsson 1983, Eriksson 1994). To the extent that these subsidies were successful in “saving jobs”, they should reduce inter-industry job turnover. Thus we include w_t, selective industrial subsidies as a proportion of industrial value added, in the regression.

The starting point for the econometric analysis is the equation

$$s = bx + e \tag{5.1}$$

where b is the coefficient vector, x the matrix of observations on the independent variables (q, *U/V* alternatively $\hat{L}$, and w) and e a vector of disturbances. Since our dependent variable is bounded within the interval $0 \leq s \leq 2$, we use a logistic functional form[6] (Kmenta 1971) to ensure that our predicted values fall within this interval:

$$g = \ln\left(\frac{s}{2-s}\right) = xb + e \qquad (5.2)$$

which may be estimated by OLS.

Table 5.1 Determinants of net inter-industry job turnover in the Swedish manufacturing industry 1965-1996

	Dependent s_t	Dependent s_t	Dependent s_t	Dependent g_t	Dependent g_t	Dependent g_t
q_t	0.068 (2.76)	0.066 (2.86)	0.070 (3.31)	1.202 (2.77)	1.156 (2.84)	1.300 (3.36)
$\Delta(U/V)_t$	0.001 (1.92)			0.011 (1.95)		
$\hat{L}_t$		-0.001 (-1.85)	-0.001 (-2.25)		-0.021 (-1.87)	-0.024 (-2.35)
Δw_t	-0.001 (-0.58)	-0.002 (-0.78)		-0.024 (-0.66)	-0.030 (-0.86)	
w_t			-0.001 (-1.32)			-0.019 (-1.16)
$\bar{R}^2$	0.188	0.214	0.306	0.194	0.216	0.311
F	3.32	3.63	5.40	3.40	3.67	5.52
Durbin-Watson	1.304	1.261	1.326	1.343	1.317	1.35
Breusch-Godfrey	2.60	3.96	3.37	2.13	3.18	2.95

t-values in parenthesis. The critical values on the five percent significance level for the Breusch-Godfrey test is 3.84 and for the Durbin-Watson test are d_l 1.244 and d_u 1.650, with the null hypothesis no autocorrelation.

Prior to the estimation of the model we test each variable for stationarity (see Appendix). All variables appear stationary except for $(U/V)_t$ and w_t which are $I(1)$, i.e. we obtain stationarity for these two variables by first-differencing each of them. However, according to the discussion in Appendix A3 we also estimate the model assuming that all variables are stationary.

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[6] $s = \dfrac{2}{1+e^{-xb-e}}$ which we linearize to obtain (5.2)

The positive and significant coefficient of q_t implies that the larger the dispersion among industries of the change of gross profit margins, the higher was the rate of inter-industry job turnover; this confirms the predictions of the model in section 3. Further, we find a positive and weakly significant relationship between s and $\Delta(U/V)$, the change in the ratio of unemployment to vacancies (excess supply/demand of labor). The rate of inter-industry job turnover has been higher in periods with a declining economic activity and increasing excess supply of labor. Hence, the countercyclical pattern of inter-industry job turnover in Swedish manufacturing resembles the pattern that Davis et al. (1996) found in the U.S. data.

Substituting the rate of change of industrial employment, $\hat{L}_t$, for $(U/V)_t$ as an indicator of labor demand conditions gives basically the same result. It may be argued that q_t and $\hat{L}_t$ are actually endogenous which would generate inconsistent OLS estimates. A test for this using lagged values as instruments does not point to serious endogeneity problems in this model.

Our data do not confirm the hypothesis that the expansion of subsidies in the 1970s, the main objective of which was to save firms from going out of business and to reduce or at least postpone layoffs, had any influence on the net inter-industry job turnover in manufacturing. The coefficient of Δw is negative but never significant.[7] This may be due to errors in estimating the “subsidy equivalent” of different measures.

For the regressions in columns 1, 3 and 4 in Table 5.1, the Durbin-Watson statistic falls into the inconclusive region. However, according to the Breusch-Godfrey test we cannot find evidence of serial correlation. Plotting the standardized residuals (see Appendix) confirms the results of the Breusch-Godfrey test. On the other hand, column 2 shows unanimous sign of autocorrelation.

Reestimating the linear equation with Huber standard errors, taking account of heteroskedasticity, or estimating a robust regression, assessing lower weight to influential observations, does not change the results. The reestimation of the model using the logistic functional form of the dependent variable gives the same results. Finally, it appears that the results are insensitive to whether we view w_t to be $I(1)$ or $I(0)$.

6 Internationalization and inter-industry job turnover

The degree of openness – i.e. exposure to international competition – as well as changes in international competitiveness of firms and industries may affect the rate of both inter- and intra-industry job turnover in an economy. According to the specific factors model in section 3, increasing world market prices and/or technical progress in domestic firms improves the ability to pay for labor in a particular industry and increases its share of employment. Price changes may be due to shifts in the product composition of world demand. Given demand, inter-industry job turnover is a function of shifts in relative international competitiveness among industries. Improving competitiveness by domestic technical progress (increasing t in (3.1)) at constant world demand and technology – so that p_i is constant – will increase employment in the *i*th industry. On the other hand, technical progress abroad, lowering p, while t is unchanged, will worsen competitiveness and reduce employment.

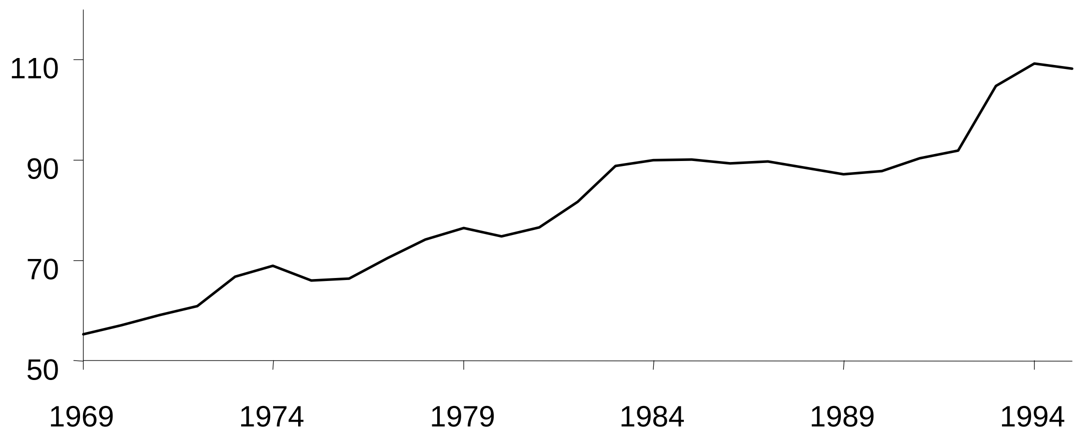
An increase in the trade ratio of an economy, defined here as the sum of exports and imports of manufactured goods as a proportion of domestic consumption of manufactures, implies an increased international specialization. This will result in a reallocation of jobs among industries to the extent that there has been increased inter-industry specialization, i.e. increasing exports in some industries and increasing imports in others. If, on the other hand, the increased specialization is mainly of the intra-industry kind, i.e. a parallel increase in exports *and* imports in most industries, it will not necessarily lead to more inter-industry turnover of jobs.

Moreover, as demonstrated in section 3, one may argue that not only the *change* but also the *level* of trade and exposure to international competition could affect the rate of job turnover. The reason is that supply shocks (technical progress) will have greater effects on employment in open sectors trading at given prices, and that a given pattern of shocks in world market prices will result in more turnover of jobs, the higher the number of sectors open to trade at given prices. Consequently, the dispersion of changes in profit margins across industries will grow with the level of internationalization.

[7] Neither is if substituted for Δw in the equations in Table 5.1.

According to Figure 6.1, the openness to international competition in the Swedish industry has gradually increased over a long period of time. The ratio of exports plus imports to domestic consumption of manufactures (T) doubled from 1969 to 1995. However, as shown by Fuentes-Godoy et al. (1996), almost all of the increase in the trade ratio in Swedish manufacturing during the period consisted of increased intra-industry trade (on the 4 digit level of ISIC), i.e. a simultaneous increase in both exports and imports in most industries. Consequently the effect of ΔT on σ has probably been small.

Figure 6.1 Exports plus imports, percent of consumption of manufactured goods 1969-95.



Even so, the increased *level* of exposure to international competition, measured by the level of the trade ratio, may have contributed to increasing inter-industry job turnover via a growing dispersion in changes in profit margins across industries. According to Table A3.1 in the Appendix, T may contain a unit root but is a difference-stationary variable. Following the discussion in Appendix A3 we estimate the effect of trade on θ using alternatively the level T and the change ΔT of trade.

The results in the first two columns of Table 6.1 show that the level of trade seems to have had a positively significant influence on the variability of profit margins. The trade level explains almost half of the variation in θ, which gives some support for the idea that the process of internationalization of the Swedish economy may have contributed to the increasing rate of inter-industry job turnover.

Column 3 shows the results using the first-differenced values of trade. There appears to be no significant relationship between ΔT and q, which is to be expected given the findings of Fuentes-Godoy et al. (1996) that most of the increase in trade has been of the intra-industry kind. There is further strong evidence of autocorrelation in column 3 of Table 6.1, implying misspecification of the model. Thus, the results in Table 6.1 should be interpreted with care.

Table 6.1 The relationship between the trade ratio in manufacturing and the variability among industries of changes in profit margin, 1969-1995

	linear	loglinear	linear
Trade ratio T	0.004 (4.69)	1.183 (4.97)	-
Change in trade ΔT	-	-	0.003 (0.77)
$\overline{R}^2$	0.447	0.477	-0.017
F	21.97	24.74	0.589
Durbin-Watson	1.52	1.44	1.04
Breusch-Godfrey	1.60	2.15	6.23

However, even for a given level of the aggregate trade ratio, job turnover will be directly affected by the actual shifts in relative international competitiveness or comparative advantage among industries. Define revealed international competitiveness (cf Balassa´s (1965) term revealed comparative advantage) in the *i*th industry as the ratio of domestic production Q_i to domestic consumption C_i, the latter defined as

$$C_i = Q_i + M_i - X_i \tag{6.1}$$

where X_i, M_i are exports and imports of the *i*th good. Then

$$\tilde{r}_i = \frac{Q_i}{C_i} = \frac{C_i - M_i + \sum_j^{n_i} X_{ij}}{C_i} = h_i + \sum_j^{n_i} x_{ij} c_{ij} \tag{6.2}$$

where $x_{ij} = \frac{X_{ij}}{C_{ij}}$ and $c_{ij} = \frac{C_{ij}}{C_i}$ are market shares on the *j*th market and the relative size of that market; h_i is the home market share. Thus, revealed competitiveness is defined as an index of market shares.

The role of shifting relative competitiveness for inter-industry job reallocation may be demonstrated by decomposition of the expression for the employment share of the *i*th industry. Omitting the time index we have:

$$a_i = \frac{L_i}{\sum_i^n L_i} = \frac{L_i}{Q_i}\frac{Q_i}{C_i}\frac{C_i}{\sum_i^n C_i}\frac{\sum_i^n C_i}{\sum_i^n Q_i}\frac{\sum_i^n Q_i}{\sum_i^n L_i} = \lambda_i \rho_i c_i \tag{6.3}$$

where $$\lambda_i = \frac{L_i}{Q_i}\frac{\sum_i^n Q_i}{\sum_i^n L_i} \qquad \rho_i = \frac{Q_i}{C_i}\frac{\sum_i^n C_i}{\sum_i^n Q_i} \qquad c_i = \frac{C_i}{\sum_i^n C_i} \tag{6.4}$$

The employment share depends on the budget share of the *i*th good (c_i), the international competitiveness of domestic producers (ρ_i), and the labor required per unit of output (λ_i, the inverse of labor productivity), the last two adjusted for the manufacturing average. The change in employment share, disregarding second order terms, may then be written as the sum of three effects: the competitiveness effect, the demand or market effect and the productivity effect:

$$\Delta a_i = \lambda_i c_i \Delta\rho_i + \lambda_i \rho_i \Delta c_i + c_i \rho_i \Delta\lambda_i \tag{6.5}$$

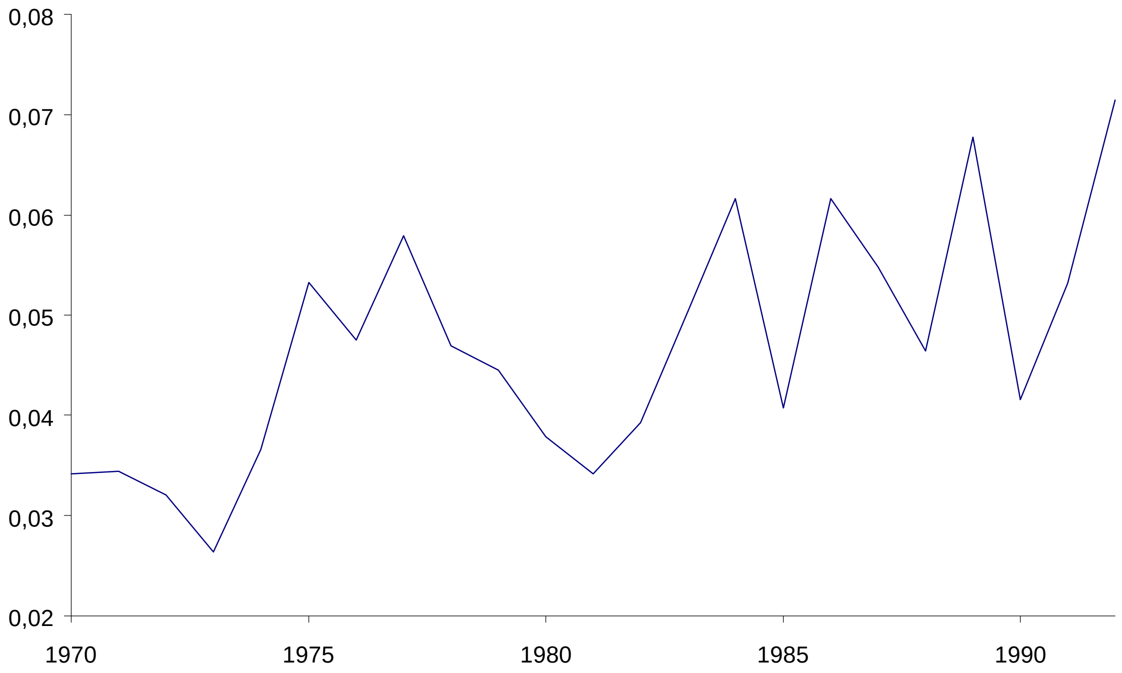
The rate of inter-industry job turnover depends on the *variation* among industries with respect to demand growth, productivity growth and change of international competitiveness (change of market shares); the larger the differences across industries in these respects, the higher will be the rate of industrial restructuring and job turnover.

The effect of changing relative international competitiveness for job reallocation among industries may then be evaluated by calculating the hypothetical value of the job turnover rate for a given period, obtained by keeping budget shares and productivity constant:

$$\sigma^* = \sum_i^n \left|\Delta a_i^*\right| = \sum_i^n c_i \lambda_i \left|\Delta\rho_i\right| \tag{6.6}$$

and comparing this – e.g. job reallocation caused by the competitiveness effect alone - with the σ according to (2.5) which is the result of all three effects combined. The result is shown in Figure 6.2.

Figure 6.2 The effect on the rate of inter-industry job turnover in Swedish manufacturing of shifting "revealed" international competitiveness 1970-92



The mean value for this variable is 0.046. Comparing this to the mean of the "actual" s computed for the same period and on the same level of aggregation (4-digit SNI), which is the result of dispersion among industries with respect to all three factors creating turnover, i.e. changes in expenditure shares, labor requirements and competitiveness (cf. (6.5)), which is 0.041, it would appear that shifting competitiveness alone did account for more than 100% of actual job turnover! It should be remembered, though, that this is the result of a purely mechanical excercise disregarding possible links between the changes. It may well be that industries with large productivity increases, i.e. large negative Δl_i s, tend to improve competitiveness (large positive Δr_i s), so that the effects partly cancel out.

Moreover, it is clear from Figure 6.2 that $s*$ tends to grow over time. Our interpretation is that an increasing volatility with respect to shifts in "revealed" competitiveness has contributed to the secular growth in the rate of inter-industry job turnover in Swedish manufacturing found in section 4.

7 Intra-industry job turnover among plants in manufacturing 1986-96

For the period 1986-96 it is possible to calculate job creation, destruction and turnover among plants within industries in the Swedish manufacturing industry.[8] Because of the change in the classification system from SNI69 to SNI92 (cf. Appendix) we work with two – partly overlapping – data panels, the first containing annual changes 1986 to 1993 for 146 industries on the 5 digit level of SNI69, the second annual changes from 1990 to 1996 for 276 industries on the 5 digit level of SNI92.

Table7.1 Intra-industry job turnover 1986-96 and its components

	1986-93		1990-96	
	Mean	Std.dev.	Mean	Std.dev
Total	0.258	0.195	0.258	0.241
Existing plants	0.156	0.105	0.154	0.124
Entry	0.050	0.082	0.050	0.111
Exit	0.052	0.073	0.055	0.103

Table 7.1 shows the mean value for s_{it} and its components, calculated according to (2.6). According to the table, on average 13% of the jobs were reallocated annually among plants within the same industry. Of this, more than half was accounted for by turnover among existing firms, while entry and exit of plants contributed about one fifth each. The mean rate of total turnover and its components were almost the same in both subperiods, but their variability was higher in the 1990s.[9] Obviously, the mean rate of intra-industry turnover among plants is much higher than reallocation among industries[10] which, as shown in section 4, was less than 3% annually.

[8] Data for job creation, destruction and reallocation on the plant level for the Swedish economy 1986-1993 have been presented by Davidsson et al. (1995) in a study focusing on the role of small firms, an issue outside the scope of this paper.

[9] Note that for overlapping years in Figures 7.1 and 7.2, the rate of job turnover and its components are generally higher when computed from data classified according to the SNI92, reflecting a finer disaggregation.

[10] This confirms the results from previous studies of job turnover, such as Davis et al. (1996) for the US and Davidsson et al. (1994) and (1995) for Sweden.

Figure 7.1 Intra-industry job turnover; total and within existing plants

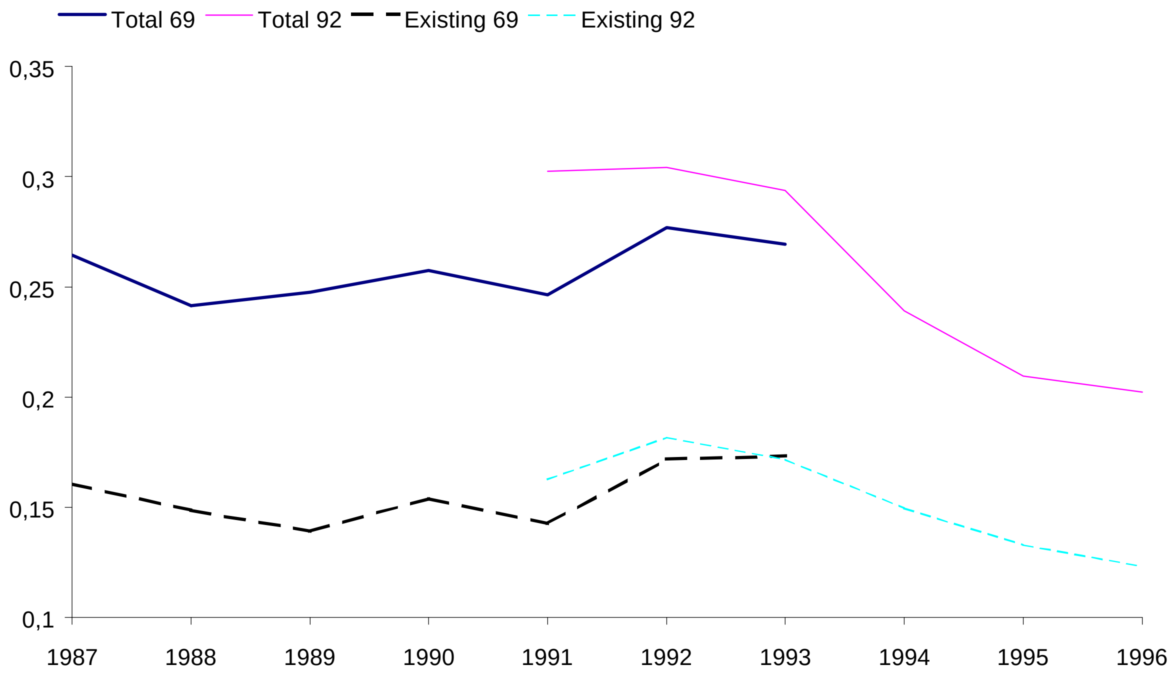
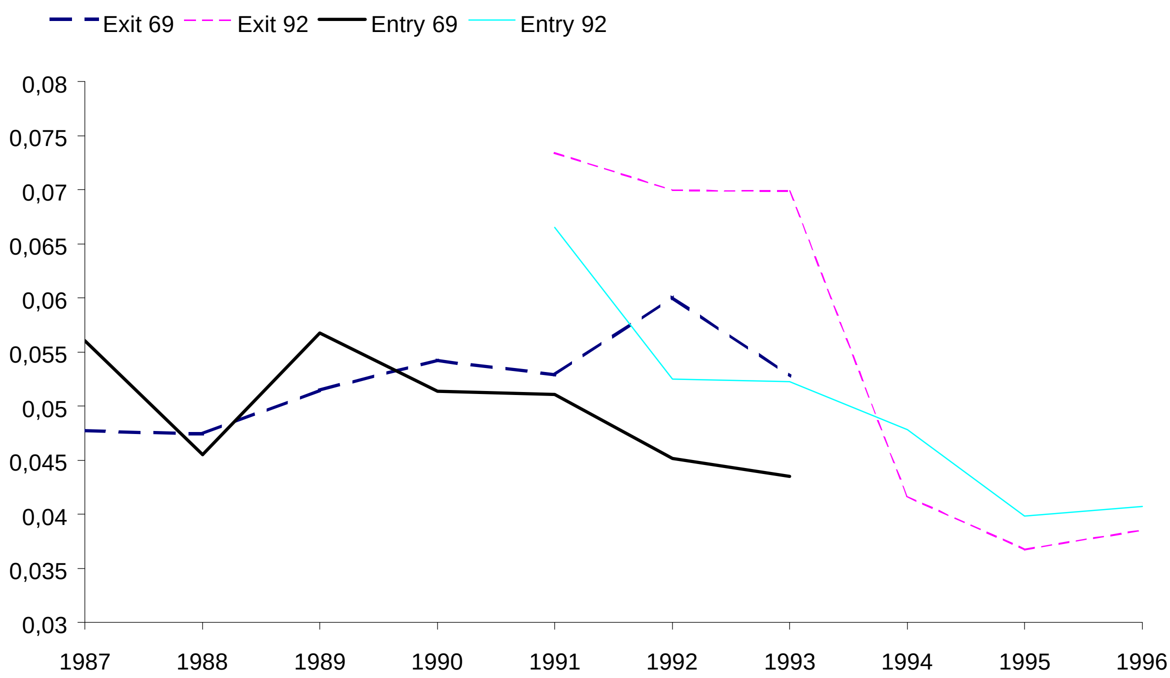


Figure 7.2 Intra-industry job turnover due to exit and entry of plants



Unlike the rate of inter-industry restructuring of employment, there seems to be no positive trend in the rate of intra-industry turnover of jobs. Figure 7.1 shows that the rate of within-industry reallocation was roughly constant up to 1991 but increased slightly in 1992, coinciding with a strong decline in total employment. This was accounted for partly by a rising exit rate,[11] which should be expected in a recession, but mainly by a higher rate of job reallocation among existing plants. Thus, both rates of turnover – inter- as well as intra-industry – show a countercyclical pattern (cf. section 5). Turnover due to entry of new plants seems to have been steadily falling since 1989.

The general impression from Figures 7.1 and 7.2 is that since the early 1990s, the rate of intra-industry job turnover has been gradually falling. This holds for each of its components, i.e. turnover within existing plants as well as turnover due to entry or exit. The process of industrial restructuring thus seems to have entered a more placid phase.

8 A framework for explaining intra-industry job turnover

For the analysis of intra-industry job turnover among firms or plants within the same industry, we need a different theoretical framework from that in section 3. Obviously, models with identical firms and perfect competition cannot contribute much toward the understanding of such job flows.

Assume an industry with monopolistic competition. Firms[12] produce differentiated products but are otherwise identical in the long run, in the sense that the systematic (non-stochastic) parts of demand and cost functions are identical. In the short run, however, the demand for the product of a particular firm is affected by firm specific random shocks ε_{jt} with mean equal to one and constant variance. The marginal revenue of the *j*th firm of industry *i* in period *t* may be written as

$$r_{ijt} = \varepsilon_{ijt} F_i(q_{ijt}) \tag{8.1}$$

where $F_i(\cdot)$ is constant across firms and over time. Profit maximization implies equality of marginal revenue to marginal cost. Assuming that in the short run labor is the only mobile factor, the firm will equate the value of the marginal product of labor with the wage rate, assumed given across firms, by adjusting employment. Using the symbols of (3.1) we may write

$$\varepsilon_{ijt} F_i(q_{ijt}) t_{ijt} f_L(L_{ijt}) = w \tag{8.2}$$

[11] According to the 1986-93 panel, but not according to the 1990-96 panel, where the peak was one year earlier.
[12] In this model we assume that each firm consists of no more than one plant.

Let firms be exposed both to demand shocks (e_{ijt}) and supply shocks (t_{ijt}) shifting the production function. The firm will then change employment and output so that (8.2) is again satisfied.

Obviously the size of these adjustments depends on the slopes of $F_i(\cdot)$ and $f_L(.)$. The more elastic the demand for the output of the representative firm (the flatter $F_i(\cdot)$, its marginal revenue curve) and the slower the marginal product of labor falls with increasing employment (i.e. the flatter $f_L(.)$), the higher will be the firm´s elasticity of demand for labor, and the more volatility in sales and employment one should expect, given the distribution of supply and demand shocks. This means that if we compare industries exposed to stochastic shocks with the same variance, we should expect the rate of intra-industry job reallocation among firms to be higher, the more elastic the $F_i(\cdot)$ and $f_L(.)$ curves of the representative firm.

In the empirical analysis of intra-industry job turnover we will not be able to measure demand and supply shocks directly. Thus we cannot explain differences across industries in rates of job turnover directly in terms of differences in the volatility of shocks. Nor will we – as we may when addressing inter-industry job reallocation – be able to measure the shocks indirectly by focusing on the resulting changes in gross profit margins, since we do not have data for profit margins on the plant level.

Consequently our empirical analysis is much more limited in scope. We ask two questions. First, which industries are likely to be exposed to high volatility with respect to demand and supply shocks to the individual firm, i.e large variance of e_{ijt} and t_{ijt}? And second, given the patterns of demand and supply shocks, in which kind of industry should we expect to observe the largest effects in terms of reallocation of employment among plants? As shown above, the answer to that is a matter of the elasticities of marginal revenue and marginal cost. However, since these elasticities cannot be measured directly, what we actually do is to explore the relationship between the rate of intra-industry job turnover and a set of industry characteristics expected to be related to the elasticities of marginal revenue and cost.

We will argue that in general one may expect a higher volatility for both demand and supply shocks in product groups in the early stages of the life cycle, rather than in more mature industries. Such markets are characterized by high rates of product development and process innovations, and differentiated demand where fashion and brand images are important, thus making both supply and demand conditions inherently unstable. There are no sufficiently disaggregated data on innovations or R&D. Further, product differentiation is notoriously difficult to measure (Caves & Williamson 1985). However, by definition such industries tend to have high rates of market growth.

The Marshall (1890) rules state that the elasticity of demand for labor of a firm will be higher, the higher the elasticity of substitution of labor for other factors of production, the higher the share of wages in total cost, and the more elastic the demand for the firm´s product (Sapsford & Tzannatos 1993). On the level of aggregation used in this paper, there are data for wage shares but not for elasticities of factor substitution.

The slope of the marginal revenue curve $F_i(\cdot)$ depends on the perceived price elasticity of demand for the product of the representative firm. When the number of firms is large, this equals the elasticity of substitution between each pair of products in the industry (Helpman & Krugman 1985). Thus, $F_i(\cdot)$ is flatter the closer substitutes – i.e. the less differentiated – products are.

If the number of firms is small, the perceived elasticity of demand will reflect the firm´s conjectures about the reactions of its competitors to changes in its price and/or sales. In the case of Cournot competition among identical firms the demand elasticity of the firm will be proportionate to the number of sellers (Richardson 1989). In general, perceived demand will be inelastic if firms expect competitors to follow their price changes (Helpman & Krugman 1989). Awareness of such retaliation should be more likely in highly concentrated industries with few sellers. A tendency for higher market share stability in concentrated industries was found for the U.S. by Gort (1963) and Caves & Porter (1978), and for Canada by Baldwin & Gorecki (1994); see also Schmalensee (1989).

An appropriate measure of market concentration, disregarding imports, could be a Herfindal index of domestic sales concentration among domestic firms. Lacking such data, one may instead use a measure of concentration of domestic production, including exports,[13] or simply the number of firms or plants in the industry; the latter may underestimate concentration.

This presumes that firms behave in a non-cooperative fashion. Given the patterns of stochastic shocks, the stability of market shares of firms within an industry may be expected to be higher in industries where there is some form of collusive behavior. The typical price cartel attempts to keep prices high by carving up the market among the participants. According to Tirole (1988) and Jaquemin & Slade (1989), tacit collusion will be simpler to enforce, and thus should be more frequent, in strongly concentrated industries where firms and products are relatively homogeneous, where (firm specific) technical progress is slow, and where MC curves are steeply rising, and MR curves steeply falling.

So far the number of firms have been assumed to be fixed. However, intra-industry job reallocation is affected also by entry and exit of firms. High barriers to entry are likely to be found in production with strong economies of scale and high minimum efficient scale (MES), and therefore with high initial investment requirements which may imply high sunk costs and thus more risky projects (Devine et al. 1985, Tirole 1988).

There are no proper measures of MES of plants on the detailed industry classification used here. Assuming a market outcome where the actual distribution of plant size in an industry will be concentrated around the MES, we may use average plant size, in terms of output or employment by plant. A negative relationship between plant size and entry of new firms was found for Sweden by Hause & Du Reitz (1984).

We will argue here that not only the *level* but also the *change* in trade and exposure to foreign competition in an industry will have a positive effect on the rate of within-industry job turnover. An increase in the trade ratio of an industry, caused by a parallel increase in exports and imports of the *i*th good, will give increased intra-industry turnover of jobs among plants, provided that the increase in specialization does not take place within firms and plants. This might occur in industries consisting of very large and differentiated plants.

[13] Since there are no data on exports by firm and plant, domestic sales by firm and thus concentration cannot be calculated.

There may be two reasons for expecting higher rates of intra-industry job turnover in industries that are exposed to international competition on the export and/or home market. One is that the demand curve of the representative firm may be more volatile, i.e. that the variance of the stochastic disturbances e_{ijt} in (8.1) may be higher than in sheltered sectors.

The other is that, for a given number of domestic producers and sellers, the market power of the representative firm is inversely related to the market share of imports. This means that the perceived elasticity of demand for the representative firm is positively related to imports and thus that the effects of given demand and supply shocks on employment will be larger. A negative effect of import competition on mark-up and market power was found for the Swedish case by Hansson (1992).

9 Determinants of intra-industry job turnover

From the discussion in section 8 we expect the rate of intra-industry job turnover s to:

1. increase with the number of plants in the industry N, where few plants is supposed to reflect seller concentration and market power of firms, as well as the likelihood of tacit collusion, resulting in steep demand curves and a high stability of market shares;
2. decrease with average plant size S, implying large minimum efficient scale and high entry barriers;
3. decrease with p, the share of non-wage value added, since the elasticity of demand for labor increases with the share of wages in total costs; p may also reflect a high mark-up of price over marginal cost and strong market power;
4. increase with the rate of growth of employment $\hat{L}$, reflecting high volatility of demand and supply shocks in early stages of the product cycle;
5. increase with the *level* of trade, first because the volatility of shocks may be higher when firms compete in international markets or with imports than for firms in sheltered sectors, and second, because given the number of domestic firms, market power will be eroded by import competition. Trade is measured by *m*, import share of consumption, and *x*, export share of production,
6. increase with an *increase* in trade ($\hat{m}, \hat{x}$), unless increased specialization takes place within firms.

A description of data and methods may be found in the Appendix. We work with two (partly overlapping) data panels, 1986-93 and 1990-96. For most of our variables the frequency distributions are strongly positively skewed, i.e. there are a limited number of extreme outliers. We know (cf. Appendix) that some of the variables, in particular employment growth and the trade ratios, are likely to contain measurement errors that may be especially serious for small industries.

We adress this problem by using weighted least squares regression (WLS) where observations are weighted by employment in order to reduce the noise due to errors that are likely to be concentrated in small industries (Berman et al. 1994). Moreover, we exclude observations with extremely high values of the trade ratios and very large changes in employment (see Appendix). We do not exclude these extreme values because they are outliers per se but on the basis that the values are economically unreasonable and hence must be due to measurement errors. However, such exclusions do not seem to affect the basic results very much. Since the dependent variable is bounded we use a logistic functional form (see section 5).

For the dependent variable and most of the explanatory variables, the major part of the variation occurs in the cross-sectional dimensions (Appendix). More important, there are reasons to believe that the effect – or even the interpretation – of some variables are different in the short and long run, i.e. in the time and cross-sectional dimensions. For example, in a comparison across industries p may reflect capital intensity, while in the short run it shows fluctuations in profits. Whereas $\hat{L}$ in the cross-section may be related to stages in the life cycle of the product, variations over time simply reflect the business cycle. For this reason we will argue that, as a complement to the fixed effect estimates, focusing on the within-industry variation of the variables, one should also look at the cross-sectional patterns obtained by the between-industry estimator (see Appendix).

Table 9.1 Determinants of rates of intra-industry job turnover in Swedish manufacturing 1986-93

	WLS	FEM	BEM	REM
Nr of plants *N*	0.046 (2.71)	-0.570 (-3.09)	0.612 (2.19)	0.026 (0.95)

Plant size $S = L / N$	-0.208 (-9.36)	-1.169 (-7.16)	-0.231 (-6.05)	-0.294 (-7.84)
Profit marg p	0.080 (0.96)	0.370 (2.68)	-0.056 (-0.29)	0.055 (0.52)
Growth $\hat{L}$	-0.764 (-4.49)	-0.989 (-5.86)	0.224 (0.43)	-0.555 (-3.70)
Exports x	-0.042 (-1.49)	0.187 (1.68)	-0.037 (-0.76)	0.016 (0.36)
Imports m	0.075 (2.53)	-0.135 (-0.88)	0.062 (1.08)	0.004 (0.08)
$\hat{x}$	-0.079 (-0.67)	-0.072 (-0.63)	-0.401 (-1.31)	-0.127 (-1.35)
$\hat{m}$	0.284 (2.05)	0.062 (0.45)	0.946 (2.03)	0.177 (1.45)
F period dummies		0.11 (excl.)		(excl.)
$\overline{R}^2$	0.294			
F	41.88	9.08	13.26	
c^2				125.70
H				64.61
LM				58.03
Nr of obs	785	785	785	785

Notes: All variables are in logarithms. The dependent variable is $g = \ln(s/(2-s))$. Observations with negative consumption, profit margins outside the interval zero to one, export and import ratios above two, or where employment more than doubled/halved in one year, have been dropped. WLS, FEM, REM and BEM are weighted regression (observations weighted by employment size), panel regression with fixed (within-industry) and random effects and between-industry estimates. Period dummy variables were found not significant according to an *F* test and were not included. *t* values in ( ).

Table 9.2 Determinants of rates of intra-industry job turnover in Swedish manufacturing 1990-96

	WLS	FEM	BEM	REM
Nr of plants N	0.097 (5.24)	0.021 (0.17)	0.168 (5.91)	0.143 (5.23)
Plant size $S = L / N$	-0.200 (-9.44)	-0.542 (-4.48)	-0.293 (-7.25)	-0.333 (-8.97)
Profit marg	-0.224	-0.250	0.185	-0.156

p	(-3.38)	(-3.24)	(1.40)	(-2.33)
Growth $\hat{L}$	-0.530 (-3.88)	-0.395 (-2.83)	-1.256 (-2.80)	-0.333 (-2.66)
Exports x	-0.080 (-3.09)	0.066 (0.82)	-0.101 (-2.00)	-0.043 (-1.07)
Imports m	0.123 (4.74)	-0.172 (-1.63)	0.082 (1.50)	-0.002 (-0.04)
$\hat{x}$	-0.008 (-0.09)	-0.066 (-0.86)	-0.111 (-0.39)	-0.122 (-1.88)
$\hat{m}$	0.103 (1.23)	0.122 (1.46)	1.135 (0.53)	0.197 (2.77)
F period dummies		13.46		
$\overline{R}^2$	0.288			
F	59.24	11.56	26.87	
c ^{2}				331.4
H				23.03
LM				190.9
Nr of obs	1151	1151	1151	1151

Notes: see table 9.1. Period dummy variables were found to be strongly significant and were included in the FEM and REM equations.

Since we lack data on the ultimate determinants of job turnover, i.e. the demand and supply shocks, as well as on the appropriate elasticities, and since our variables are but imperfect proxies of the corresponding theoretical concepts, one should not expect our equations to explain all variation in s across industries and over time. The $\overline{R}^2$ s in the WLS equations are slightly below 0.3. However, all regressions are strongly significant.

There appears to be a time pattern common to all industries in the second panel but not in the first, which is not surprising considering the strong macroeconomic fluctuations in the 1990s. The Breusch-Pagan (*LM*) tests indicate the presence of industry specific effects, i.e. cross-sectional effects of omitted variables, potentially creating bias in pooled regressions. On the other hand, the fixed effects (*FEM*) regressions, focusing on within-industry variation over time, produce estimates widely differing from the rest, especially for *N*, p , *x* and *m*, which may imply that the long run effects across industries are in fact different from the short run effects over time. Finally, the Hausman (*H*) tests imply – strongly for the first period, less clear in the second – that the random effects (*REM*) equations may be misspecified. This seems likely, considering that we have not been able to measure the ultimate determinants of job turnover.

Summing up the results from Tables 9.1 and 9.2 we find that the rate of job turnover among plants within an industry, σ, has been higher,

1. the higher the number of plants *N* in the industry; the coefficient is positive and strongly significant except for the FEM estimates;
2. the lower the average plant size $S = L / N$ measured by employment; the coefficient is negative and strongly significant in all regressions;
3. the lower the average gross profit margin or mark-up π measured as non-wage share of value added in the industry. The coefficient is negative and strongly significant (except for BEM) but only in the second panel; for the first panel there seems to be no negative effect at all.

These results confirm our hypotheses. Our interpretation is that the results reflect the role of market power, based on seller concentration, tacit collusion and entry barriers, to create stability of market shares, as well as the “Marshall rule” that the elasticity of labor demand should be lower in capital intensive industries. The effects, in the form of structural adjustment and job turnover among firms and plants within an industry, of given supply and demand shocks seem to be larger the more competition there is in the market.

Other results are less clearcut and/or contrary to expectations. The coefficient of the employment growth variable is negative, contrary to the hypothesis, and strongly significant (except for BEM in the first panel). Thus, the product cycle argument in section 8 obtains no support. We believe that the data (exept in the BEM case) actually capture the effect of business cycle fluctuations on job creation and destruction over time.[14] Thus, not only inter-industry (see section 5) but also intra-industry job turnover seems to follow a counter-cyclical time pattern.

We expected the level, as well as the increase, of trade to be positively related to the rate of intra-industry job turnover. The results are somewhat mixed. The *level* of import penetration (m) appears to increase the rate of intra-industry job turnover, but the coefficient is significant only in the weighted regressions. The interpretation may be that a high degree of import competition reduces firms´ market power and increases the perceived elasticity of demand for individual products. High import penetration may also increase the volatility of demand shocks.

Increasing import penetration seems to cause more job turnover among plants in an industry. The coefficient is positive and significant in three of the equations. The negative employment effects of an increasing import competition in an industry seem to be disproportionately distributed among firms.

Somewhat unexpectedly it turns out that export orientation (x) seems, if anything, to have a negative effect on job reallocation, contrary to the hypothesis. This holds also for the increase in export share. The coefficients are mostly negative, though significant only in one case. Why market shares in strongly export oriented industries should be more stable than in other sectors is not easy to explain in a theoretically satisfactory way.

We may, however, offer a tentative explanation based on the market behavior of certain Swedish export industries. Nordic pulp and paper producers have repeatedly been accused by the European Commission of forming price cartels, carving up the market for their exports to the EU. Moreover, expansion of capacity by investment in the forest products industry tends to be lumpy, in the sense that all the large companies tend to make huge investments at the same time. This may explain why employment shares are relatively stable at least in some strongly export oriented industries, and why export market growth seems to benefit all firms to the same extent.

10 Conclusions: competition and job turnover

We found that the rate of inter-industry job turnover in the Swedish manufacturing industry, which in 1964-96 on average corresponded to 2.7% of the stock of jobs in manufacturing

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[14] For those regressions including period dummies $\hat{L}$ captures the effects of industry specific cyclical changes in activity, which need not be perfectly syncronized with the overall business cycle.

annually, did show a positive trend over the period. Thus in a historical perspective, the mid-1970s do not stand out as such an exceptional period of industrial restructuring as was thought at the time. The time pattern of job reallocation seems to be counter-cyclical.

Actual job turnover is the result of adjustment pressure and resistance. Focusing on the former, we found the rate of inter-industry job turnover to be driven by the dispersion across industries in the change of the profit margins; the more profit changes differ, the more turnover, confirming our model. Our results indicate that shifts among industries in international competitiveness, which seems to have been increasing over time, did play a central role for the level, as well as for the trend, of the rate of inter-industry job turnover.

The rate of intra-industry job turnover among plants within industries was much higher; the annual average in 1986-96 was around 13% of the stock of jobs in the typical industry. More than half of this was reallocation of jobs among existing plants, while entry and exit of plants contributed about one fifth each. Unlike the reallocation among industries it displays no trend. Since the early 1990s, within-industry job turnover has been falling; this is also true for its components, i.e. reallocation among existing plants and turnover due to entry and exit.

The results of the econometric analysis indicate that the rate of intra-industry job turnover among plants tends to be high in industries consisting of many small plants, with low gross profit margins (mark-ups) and where domestic firms are exposed to import competition. Our interpretation is that this reflects the limited market power of firms in such industries, which means that market shares and the distribution of employment will be highly sensitive to firm specific demand and supply shocks.

Appendix

A1 The Ricardo-Viner model

Assume n sectors, each producing a homogeneous good using labor L, which is perfectly mobile across sectors, so that the wage w is the same, and capital K_i which is sector specific in the short run. All goods are traded on the world market at given prices p_i. Perfect competition in all markets implies

$$w = p_i t_i f_L^i(L_i, K_i) \qquad \text{(A1.1)}$$

where t_i is a technology shift parameter and $t_i f_L^i(L_i, K_i)$ the marginal productivity of labor. With the K_i :s fixed, labor demand depends on product price, wage rate and technology:

$$L_i = L^i(p_i, w, t_i) \qquad \text{(A1.2)}$$

From (A1.1), technical change dt_i will have the same effect on labor demand as a price increase dp_i.

Define the elasticity of demand for labor λ_i by

$$\hat{L}_i = \lambda_i(\hat{p}_i - \hat{w}) \qquad \text{(A1.3)}$$

where $\hat{L}_i, \hat{p}_i, \hat{w}$ indicate rates of change: note that λ_i is defined to be positive. The change in the share of employment of the *i*th industry will be

$$da_i = a_i(\hat{L}_i - \hat{L}) \qquad \text{(A1.4)}$$

Inserting (A1.3) into (A1.4) gives

$$da_i = a_i\lambda_i(\hat{p}_i - \hat{w}) - a_i\hat{L} \qquad \text{(A1.5)}$$

Set all $\lambda_i = \lambda$: then

$$\hat{L}_i = \lambda(\hat{p}_i - \hat{w}) \qquad \text{(A1.6)}$$

By definition, $\sum_{i=1}^{n} a_i = 1$ and $\sum_{i=1}^{n} da_i = 0$. Inserting (A1.6) into (A1.5) and summing across industries gives

$$\sum_{i=1}^{n} da_i = \sum_{i=1}^{n} a_i\lambda(\hat{p}_i - \hat{w}) - \sum_{i=1}^{n} a_i\hat{L} = \lambda\sum_{i=1}^{n} a_i\hat{p}_i - \lambda\hat{w}\sum_{i=1}^{n} a_i - \hat{L}\sum_{i=1}^{n} a_i = 0 \qquad \text{(A1.7)}$$

Solving for $\hat{w}$ from (A1.7) we obtain

$$\hat{w} = \sum_{i=1}^{n} a_i\hat{p}_i - \lambda^{-1}\hat{L} \qquad \text{(A1.8)}$$

The wage change is a weighted average of price changes (for L constant). Inserting (A1.8) into (A1.5) gives

$$da_i = a_i\lambda(\hat{p}_i - \sum_{i=1}^{n} a_i\hat{p}_i + \lambda^{-1}\hat{L}) - a_i\hat{L} = a_i\lambda(\hat{p}_i - \sum_{i=1}^{n} a_i\hat{p}_i) \qquad \text{(A1.9)}$$

Inserting (A1.9) into our measure of structural change and inter-industry job turnover in (2.5) we obtain

$$\sigma = \sum_{i=1}^{n}|da_i| = \lambda\sum_{i=1}^{n} a_i\left|\hat{p}_i - \sum_{i=1}^{n} a_i\hat{p}_i\right| \qquad \text{(A1.10)}$$

Define the gross profit margin in the *i*:th industry as

$$\pi_i = 1 - \alpha_i = 1 - \frac{wL_i}{p_iQ_i} \qquad \text{(A1.11)}$$

where p_iQ_i is value added. The change of the gross profit margin caused by changing prices is obtained by differentiating (A1.11) with respect to p_i, giving:

$$d\pi_i = \frac{-[p_iQ_i(L_i dw + wdL_i) + wL_i(p_i dQ_i + Q_i dp_i)]}{(p_iQ_i)^2} \qquad \text{(A1.12)}$$

Inserting for

$$p_i dQ_i = p_i f_L^i(L_i) dL_i = wdL_i \qquad \text{(A1.13)}$$

and simplifying we obtain

$$d\pi_i = \alpha_i(\hat{p}_i - \hat{w}) - \alpha_i(1-\alpha_i)\hat{L}_i \qquad \text{(A1.14)}$$

Inserting (A1.3) and setting $\lambda = 1$ gives

$$(\hat{p}_i - \hat{w}) = \frac{d\pi_i}{\alpha_i^2} \qquad \text{(A1.15)}$$

Inserting (A1.15) into (A1.5) we obtain

$$da_i = a_i\left(\frac{d\pi_i}{\alpha_i^2} - \hat{L}\right) \qquad \text{(A1.16)}$$

Solving for $\hat{L}$ from the condition that $\sum_{i=1}^{n} da_i = 0$ gives

$$\hat{L} = \sum_{i=1}^{n} \frac{a_i d\pi_i}{\alpha_i^2} \qquad \text{(A1.17)}$$

Inserting (A1.17) into (A1.16) gives

$$da_i = a_i\left(\frac{d\pi_i}{\alpha_i^2} - \sum_{i=1}^{n} \frac{a_i d\pi_i}{\alpha_i^2}\right) = \phi_i \qquad \text{(A1.18)}$$

From (A1.18) we obtain an expression for σ, the rate of inter-industry job turnover:

$$\sigma = \sum_{i=1}^{n} |da_i| = \sum_{i=1}^{n} a_i \left| \frac{d\pi_i}{\alpha_i^2} - \sum_{i=1}^{n} \frac{a_i d\pi_i}{\alpha_i^2} \right| = \sum_{i=1}^{n} \phi_i = \theta \qquad \text{(A1.19)}$$

A2 Inter-industry job turnover: the data

The time series presented in Figure 4.1 for σ has been calculated according to equation (2.5) from employment data by industry from the Swedish industrial statistics on the most detailed level available. For 1964-91, employment data are given for 160 industries on the 6-digit level of SNI69 (which is identical to ISIC on the 4-digit level). This curve has been reproduced in Figure A2.1. For comparison, we have also calculated σ for 76 industries on the 4-digit level. By definition, the latter curve will lie below the former, since Δa_i of different signs in two subgroups will cancel out by aggregation. However, the two curves follow each other closely; the correlation coefficient is 0.91.

In 1990 the population definition and the sampling methods of the industrial statistics changed. Since data for 1989 were published both according to the “old” and the “new” system, it was possible to calculate σ for 1988-89 according to the old, and 1989-90 to the new system.

From 1994 the classification system was changed to the SNI92, which is based on the NACE; employment data were transformed according to SNI92 back to 1990. Our data for σ for 1991-96 (where the first value is the change from 1990 to 1991) has been calculated from employment data on the 5-digit level of the SNI92, a total of 282 industries. Since these data are much more disaggregated, the series computed from SNI69 and SNI92 are not directly comparable. For the only year when both are available, i.e 1991, the latter is 47 percent higher (Figure A2.2). To obtain an indication of the long run trend of net inter-sectoral job mobility we have linked the two series, using the relative size in 1991 as a benchmark. This may be justified by the fact that the S measures computed on different levels of SNI69 in 1964-91 follow each other closely except for the level difference (Figure A2.1).

Figure A2.1 Inter-industry job turnover 1964-91 calculated on the 6-digit (upper curve) and 4-digit (lower curve) levels of the SNI69.

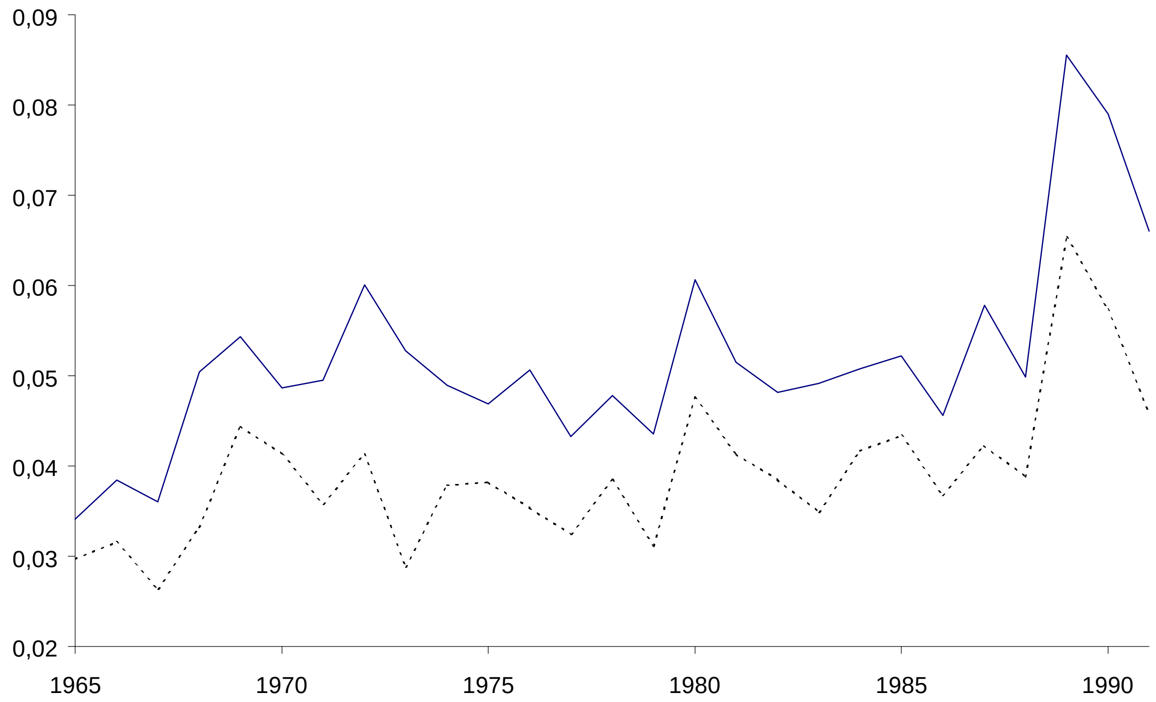
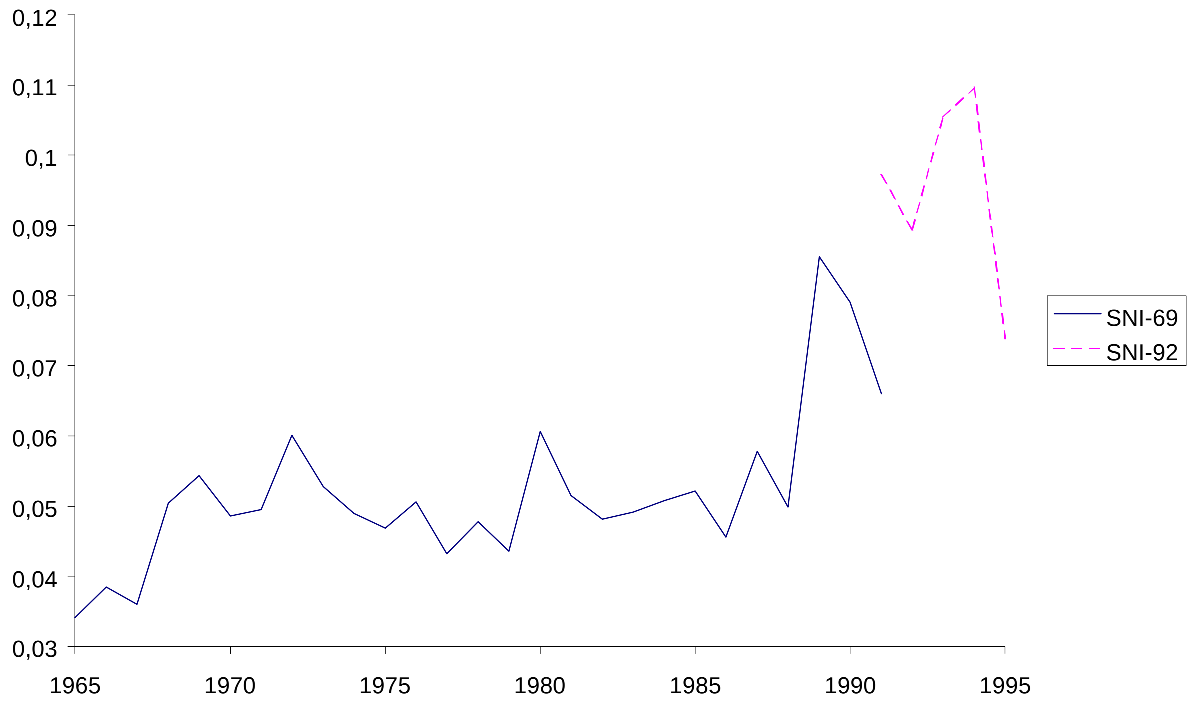


Figure A2.2 Net inter-industry job turnover 1964-96: unadjusted series. Job turnover calculated for 1964-91 on the 6-digit level of SNI69, and for 1990-96 on the 5-digit level SNI92



A3 Determinants of the rate of inter-industry job turnover, and internationalization: Model evaluation

The tests reported here refer to equations reported in Tables 5.1 and 6.1.

- **Unit Root Test**

If any of the variables contain a unit root then running a regression using such a variable would potentially create a spurious economic relationship (unless it cointegrates with other series). Hence, we test for unit roots using the augmented Dickey-Fuller test (ADF). We test

$$H_0 = \text{series contains a unit root}$$
$$H_A = \text{series is stationary}$$

We should however note that the augmented Dickey-Fuller test is based on asymptotic properties and is hence not the quite appropriate test for our small sample. In small samples the test tends to overaccept the null hypothesis of a unit root. We therefore, especially regarding equation (6.3), allow ourselves to use the test more as a guide-line than being decisive.

Table A3.1 Augmented Dickey-Fuller Test for Unit Root

Observed and critical values of the ADF	s_t	g_t	q_t	$\hat{L}_t$	$(U/V)_t$	w_t	T_t
$\tau_{obs;\ constant}$							
lagged differecne 0	-2.954	-3.068	-3.022			-1.340	-0.092
lagged difference 1				-4.262	-2.157		
$\tau_{obs;\ constant\ and\ trend}$							
lagged difference 0	-4.333	-4.410				-1.269	-1.925
lagged difference 1			-5.340	-4.455	-3.241		
$\tau_{crit;\ constant}$ 1 %	-3.6576	-3.6576	-3.6576	-3.6752	-3.6661	-3.6576	-3.7076
5 %	-2.9591	-2.9591	-2.9591	-2.9665	-2.9627	-2.9591	-2.9798
10 %	-2.6181	-2.6181	-2.6181	-2.6220	-2.6200	-2.6181	-2.6290
$\tau_{crit;\ const\ and\ trend}$ 1 %	-4.2826	-4.2826	-4.2949	-4.3082	-4.2949	-4.2826	-4.3552
5 %	-3.5614	-3.5614	-3.5670	-3.5731	-3.5670	-3.5614	-3.5943
10 %	-3.2138	-3.2138	-3.2169	-3.2203	-3.2169	-3.2138	-3.2321

Notes: For variable definitions see text.

According to the ADF we can reject the null hypothesis of the existence of a unit root in the variables g_t, q_t, $\hat{L}_t$. However, s_t is less clearcut. The null hypothesis is rejected on a ten percent significance level but very close to the critical value on the five percent significance level. The variable appears to be stationary if we allow for a deterministic trend. We may not reject the null hypothesis of the existence of a unit root in the variable $(U/V)_t$, w_t and *T*. All three variables are difference-stationary.

- **Detection of Influential Observations**

The case statistic DFBETA measures the effect on the OLS coefficient of omitting an influential observation. The observation is considered influential if it shifts the coefficient of interest by half a standard error or more. The year 1974 has a large negative influence on the coefficient of q_t, a weighted measure of the dispersion of changes in profit margins among industries, while the year 1994 has a large positive influence. The coefficient of Δw_t, the differenced series of selective industrial subsidies as a proportion of industrial value added, is largely positively influenced by the year 1984. In the regression where we substitute $\hat{L}_t$ for $(U/V)_t$ the year 1984 is the only influential observation and is found for the coefficient of Δw_t, originating from a drastic decrease in the selective industrial subsidies between 1983 and 1984.

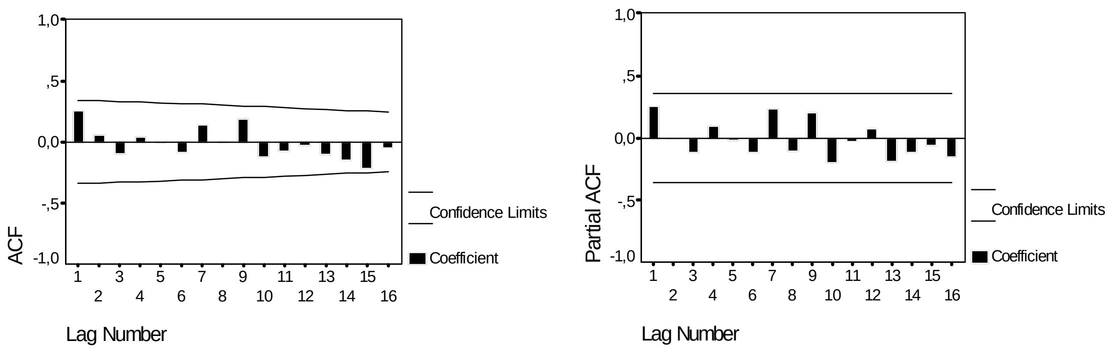
- **Sensitivity Analysis**

In our paper we use the variable w_t which measures the selective industrial subsidies as a proportion of industrial value added. We have values for this variable for the period 1976-93. For the years before and after this period the subsidies were very low. Since we do not have the exact values, we check the model's sensitivity to various approximations of these values. The results do not change much neither when w_t is excluded (same level of significance and same sign for the remaining coefficients), nor when we allow the lacking years to take values of diminishing size according to the first and last observations respectively.

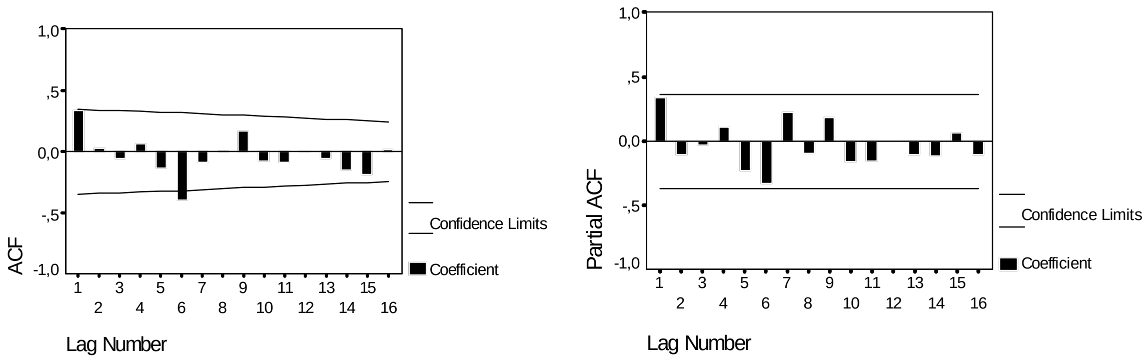
- **Autocorrelation**

In all but one version of the estimation of equation (5.1) we obtain inconsistency between the two tests of autocorrelation that we use. Hence, in order to conclude whether our residuals are autocorrelated we also plot the autocorrelation functions and the partial autocorrelation functions below.

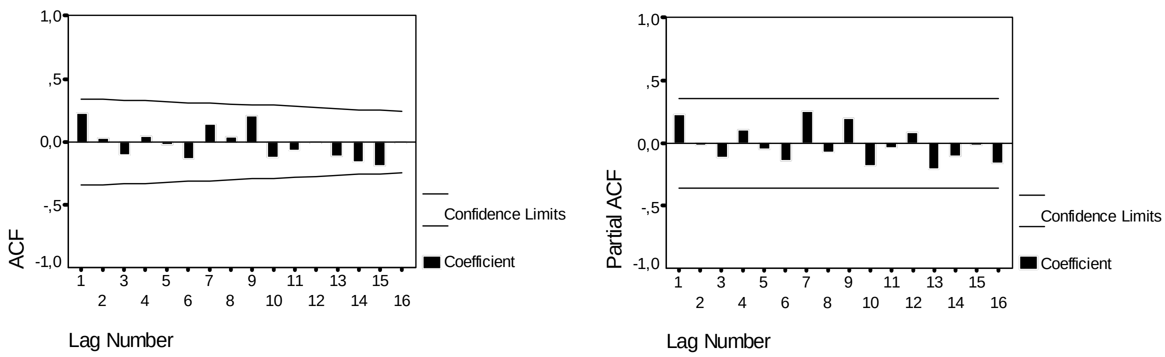
Figure A3.1 ACF and PACF plots of the OLS standardized residuals



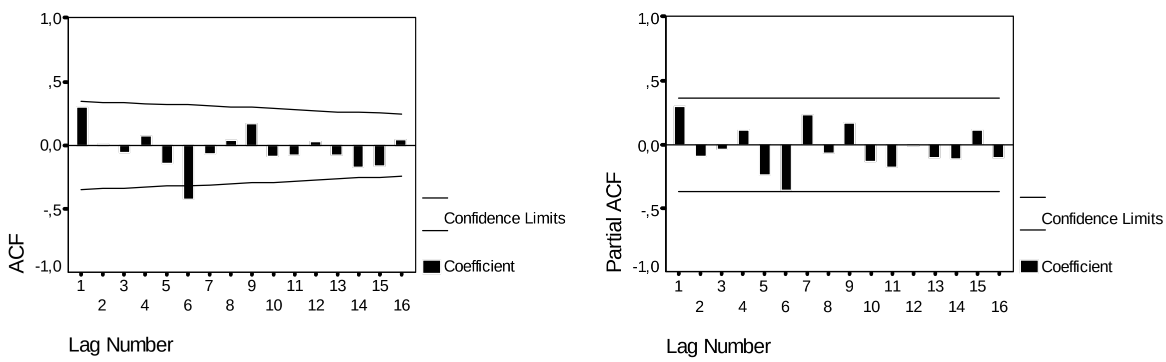
Standardized residuals from the estimation results of column I of Table 5.1



Standardized residuals from the estimation results of column II of Table 5.1



Standardized residuals from the estimation results of column III of Table 5.1



Standardized residuals from the estimation results of column IV of Table 5.1

According to Figure A3.1 models II and IV imply autocorrelation among the residuals, which is in full accordance with the Durbin-Watson and the Breusch-Godfrey statistics regarding model II. However, these two tests give different indications for the estimation results of column IV. The Durbin-Watson statistic falls into the inconclusive region while the Breusch-Godfrey statistic implies that there is no significant sign of autocorrelation among the residuals. This inconsistency could be a sign of misspecification of the model.

We also add the first lag of the dependent variable to pick up some of the autocorrelation. This improves the Durbin-Watson statistic but leaves all other indpendent variables insignificant. Moreover, models II and IV contain significant lags of order six, which may be due to business cycle variation that we have not been able to fully control for.

- **Parameter stability**

To check the parameter stability of the following model

$$s_t = a + b_1 q_t + b_2 \Delta(U/V)_t + b_3 \Delta(w)_t + e_t \tag{A3.1}$$

we perform the test statistic

$$W_r = \frac{1}{s} \sum_{r=k+1}^{r=t} w_r \ , \tag{A3.2}$$

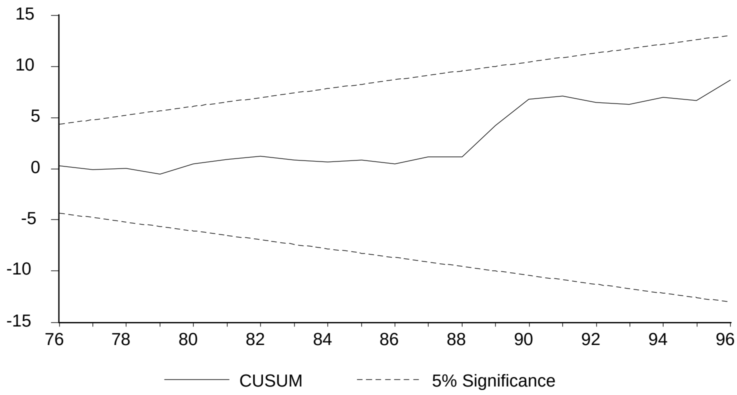
where

$$w_r = \frac{y_r - x_r b_{r-1}}{\sqrt{\left(1 + x_r\,(X'_{r-1} X_{r-1})^{-1} x'_r\right)}} \text{, and } s^2 = \frac{1}{T-k-1} \sum_{r=k+1}^{T} \left(w_r - \overline{w}_r\right)^2 \tag{A3.3}$$

The null hypothesis that we test is that the coefficient vector β is the same in every period. Under the null hypothesis $w_r \sim (0, \sigma^2)$.

Figure A3.2 depicts the CUSUM over time. We see that the values keep within the five percent significance bound. The conclusion would be that the null hypothesis of parameter stability is accepted.

Figure A3.2 Plot of CUSUM

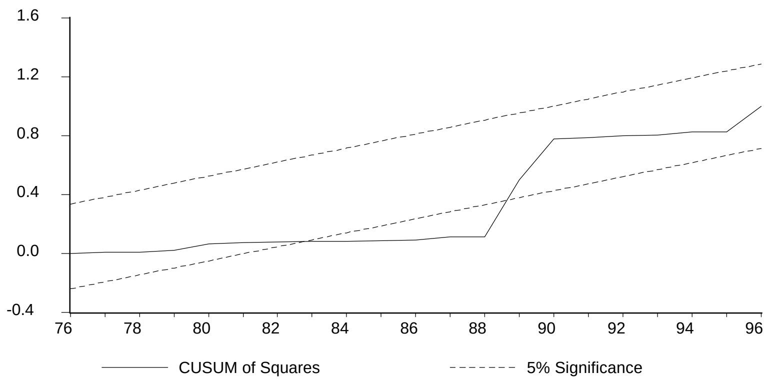


However, we also plot the CUSUMSQ as a complement to the CUSUM test. The CUSUMSQ test is a device we can use if we suspect that our β coefficients may depart from being stable in a haphazardous rather than systematic way.[15]

From Figure A3.3 we see that the curve of the CUSUMSQ does move outside the five percent confidence bound. The plot indicates that we may have instability in the period after 1980. It is interesting to note that we obtain different results from Figures A3.2 and A3.3. Brown et al. (1975) note that this could indicate that the instability may be caused by a shift in residual variance instead of shifts in the coefficients. This could be tested by using a moving regression.

[15] Brown et al. (1975)

Figure A3.3 Plot of CUSUMSQ



A4 Intra-industry job turnover: the data

Data for employment by plant and industry in Swedish manufacturing have been obtained from the data base ÅRSYS, compiled by Statistics Sweden. Plants are classified by 5-digit industry for 1986-93 according to the SNI69 (identical to ISIC to the 4-digit level) and for 1990-96 according to SNI92, which is based on NACE). Since it has not been possible to translate one classification into the other, we work with two different but partly overlapping data panels, one for 1986-93 (panel 1), the other for 1990-96 (panel 2). The calculations described below are performed on both panels.

For each industry and year we calculate the share of employment for each plant in that industry and then the change in employment share from one year to the next according to (2.6). A plant with data for employment up to and including year t , which is missing from year t+1 and after, is treated as an exit from t to t+1. A plant with positive employment from t+1, but where previous data are missing, is classified as an entry.

For our data to be economically relevant it is necessary that behind each appearance or dissappearance of a plant identity (code number) there is a ”real” change in the sense that a certain economic activity is started or closed down. A plant code number may change if the plant changes both owner and activity classification (SNI code) or address; the plant identity is thus more stable than that of the firm. For changes pertaining to larger firms there is a manual control. For small plants, however, our data for entry and exit frequencies may be somewhat overstated, to the extent that identity code numbers appear or disappear without any “real” changes taking place.

Another complication is that existing plants may change SNI code. In principle plants are assigned to industries on the basis of its (main) product(s) according to the product-industry concordance. Thus, a multi-product plant may be re-classified following a change of its product mix. One could then argue that this might be treated as a combination of an exit (in the old industry) and an entry (in the new). However, according to Statistics Sweden, most re-classifications occur because previous classifications are corrected. When calculating changes between two years we have therefore chosen to neglect changes of SNI code. The employment change of such a plant is thus classified as a change of the share of an existing plant in the “old” industry.

Changes in rules for taxation registration resulted in apparent changes in the number of plants registered in the ÅRSYS data base in 1991 and 1994. However, these changes seem to have been mostly affecting very small (one person) firms in agriculture and services (Davidsson et al. 1996). To sum up, measurement errors in the material tend to exaggerate intra-industry job mobility among plants, in particular entry and exit. It is difficult to estimate the order of magnitude of these errors. However, they are most likely to occur for small plants, and in this sense are less important. Moreover, there are no indications that the errors vary across industries and over time in a systematic way.

Panel 1 contains annual changes 1986-93 for 146 industries on the 5-digit level of SNI69, a total of 1022 observations, and panel 2 changes 1990-96 for 276 industries, with 1656 observations. Since we combine trade data with industrial statistics to calculate apparent consumption, import market shares etc., measurement errors will be introduced because there is no one to one correspondence between the classification of goods and the classification of industries. Moreover, industry data do not cover small (less than 5 employees) plants. Finally, plants may be re-classified if the output mix changes, or wrongly re-classified, All of this will distort data for employment growth by industry as well as trade ratios. Such errors are likely to be most serious for small industries.

Inspection of the data reveals that the frequency distributions of σ_{it}, the rate of intra-industry job reallocation, and its components are strongly positively skewed, in particular the distributions of entries and exits. Logarithms of these variables seem to come closer to a normal distribution. This operation means that a small proportion - 2 percent in panel 1 - of observations with zero values will be lost.

As to the independent variables, all except π, the gross profit margin, are also positively skewed, with a small number of extreme outliers. In theory, there are limits for the values that these variables may take. Consumption *c* should be non-negative, and gross profit ratios π should not exceed one. We have deleted observations with negative consumption and non-wage value added, i.e. we keep observations where $c \geq 0$ and $0 \leq \pi \leq 1$, deleting 11 observations in panel 1 and 52 in panel 2.

Disregarding re-exports and changes in stocks, the ratios of imports to consumption and exports to production should not exceed one. Measurement errors of the kind discussed above may, however, explain higher values of the trade ratios as well as extreme values of employment changes by industry. In order to produce alternative estimates, not dominated by measurement errors resulting in extreme outliers, we construct a revised version of both panels by eliminating observations with extreme values of employment changes ($\hat{L}_{it} = L_{it} / L_{it-1}$), import share of consumption (*m*) and export share of output (*x*). Thus, we keep observations for which $0.5 < \hat{L} < 2$, $0 < m < 2$, and $0 < x < 2$, deleting another 48 observations in panel 1 and 160 in panel 2. The mean for total employment in those industries (observations) deleted is about 20 percent of mean employment in the original panels, confirming our belief that outliers – which may be caused by measurement errors - are most frequent in small industries.

For the majority of the variables it appears that most of the variation occurs in the cross-sectional, rather than the time dimension. In particular, for the variables *N*, *S*, *x* and *m* the between-industry standard deviation is much larger than the within-industry deviation.

A5 Intra-industry job turnover: estimation problems

There are some features common to most of our data, each giving rise to various estimation problems:

- strongly positively skewed frequency distributions

  outliers, possibly caused by measurement errors and concentrated to small industries
- bounded dependent variable
- multicollinearity
- most of the variation occurs in the cross-sectional dimension.

Let β be a vector of regression coeffients, x_{it} a vector of independent variables varying over units and time, and ν_i, u_{it} random variables. Consider the following models (Hsiao 1986, Statacorp 1995):

$$y_{it} = \alpha + x_{it}\beta + u_{it} \qquad \text{(A5.1)}$$

$$y_{it} = \alpha_{it} + x_{it}\beta + u_{it} \quad \text{(A5.2)}$$
$$y_{it} = \alpha_t + x_{it}\beta + \nu_i + u_{it} \quad \text{(A5.3)}$$
$$y_{it} = \alpha + \bar{x}_i\beta_1 + (x_{it} - \bar{x}_i)\beta_2 + u_{it} \quad \text{(A5.4)}$$

In the first case β may be estimated by a pooled OLS regression. The second requires introduction of fixed industry and time period effects. In the third the industry effects are assumed to be random variables. The fourth equation finally shows the case where the long run, cross-sectional effects (β_1) may be different from the short run effects over time (β_2), in which case the second set of coefficients may be estimated by means of a fixed effect (within-industry) regression and the first by a between-industry regression.

An *F* test of the period dummies shows if there are common time effects. The Breusch-Pagan Lagrange multiplier (*LM*) ($H_0: \sigma_u^2 = 0$) tests for existence of random industry effects, i.e. if pooled regressions are sufficient. Finally, the Hausman test ($H_0: x_{it}, \nu_i$ uncorrelated) checks if the model is correctly specified.

All variables are expressed in logarithms, reducing the skewness. This implies losing a small number of zero observations on the dependent variable; for panel 1 about 2%.

Since our original dependent variable is bounded - $0 \le \sigma \le 2$ - we use instead as dependent variable $\gamma = \ln\left(\frac{\sigma}{2-\sigma}\right)$. The regression is derived from the logistic functional form $\sigma = \frac{2}{1+e^{-x\beta-\varepsilon}}$ where the explanatory variables *x* are expressed in logarithms.

To deal with outliers we use weighted regression where observations are weighted by size, here employment, in order to reduce the noise due to measurement errors concentrated in small industries (Berman et al. 1994). Since in the panel regressions weighting is not possible, we use a revised data set where extreme observations are excluded, as described above.

The correlation matrices for the independent variables are shown below for both panels. There are strong correlations between *S* and *N*, $\hat{x}$ and $\hat{m}$ and in particular between *x* and *m*, potentially leading to multicollinearity in our estimations. However, leaving out one in each pair of these variables does not markedly change the significance of the other.

Table A5.1 Correlation matrix for determinants of intra-industry job turnover 1986-93

	γ	$\ln N$	$\ln S$	$\ln \pi$	$\ln \hat{L}$	$\ln x$	$\ln m$	$\ln \hat{x}$	$\ln \hat{m}$
γ	1.0000								
$\ln N$	0.2768	1.0000							
$\ln S$	-0.4369	-0.5144	1.0000						
$\ln \pi$	-0.0917	-0.0987	0.1667	1.0000					
$\ln \hat{L}$	-0.1108	-0.0162	0.0239	0.2437	1.0000				
$\ln x$	0.0096	0.0861	0.0540	-0.2077	-0.0760	1.0000			
$\ln m$	0.0710	-0.0171	-0.0734	-0.2361	-0.1019	0.8325	1.0000		
$\ln \hat{x}$	-0.0426	-0.0753	0.0327	-0.1089	-0.0458	-0.1693	-0.0808	1.0000	
$\ln \hat{m}$	0.0366	-0.0077	-0.0101	-0.0368	0.0134	-0.1389	-0.1901	0.4135	1.0000

Table A5.2 Correlation matrix for determinants of intra-industry job turnover 1990-96

	γ	ln N	ln S	ln π	ln $\hat{L}$	ln x	ln m	ln $\hat{x}$	ln $\hat{m}$
γ	1.0000								
ln N	0.4112	1.0000							
ln S	-0.4800	-0.4852	1.0000						
ln π	-0.0969	-0.0705	0.1034	1.0000					
ln $\hat{L}$	-0.1267	-0.0599	0.0086	0.0804	1.0000				
ln x	-0.0886	-0.0053	0.0360	-0.1191	0.0500	1.0000			
ln m	-0.0062	-0.0821	-0.1261	-0.1230	0.0119	0.7644	1.0000		
ln $\hat{x}$	0.0432	0.0203	-0.0090	0.0048	-0.0528	-0.1983	-0.1204	1.0000	
ln $\hat{m}$	0.0712	0.0283	0.0305	0.0110	0.0183	-0.0122	-0.1112	0.4914	1.0000

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